

SUPREME COURT OF THE STATE OF NEW YORK
COUNTY OF NEW YORK

TRI-CITY, LLC; and ENDOR CAR AND
DRIVER, LLC,

Petitioners,

v.

NEW YORK CITY TAXI AND LIMOUSINE
COMMISSION and MEERA JOSHI, in her
official capacity as Chair, Commissioner, and
Chief Executive Officer of the New York City
Taxi and Limousine Commission,

Respondents.

Index No.: _____

Hon.

EXPERT REPORT OF DR. CATHERINE TUCKER

JANUARY 29, 2019

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I. QUALIFICATIONS

1. I am the Sloan Distinguished Professor of Management Science at MIT Sloan at the Massachusetts Institute of Technology (“MIT”) in Cambridge, Massachusetts. I received an undergraduate degree in Politics, Philosophy and Economics from Oxford University in the United Kingdom. I received a PhD in Economics from Stanford University in 2005. I have been at MIT since completing my PhD.
2. My academic specialty lies in studying how digital technologies have changed the economy. A particular specialty for me has been understanding how new digital technologies that help the management of platform businesses affect their performance. I teach an executive course on Platform Strategy at MIT,¹ and I am also leading the Economics of Artificial Intelligence initiative at the National Bureau of Economics Research.
3. I am an Associate Editor at Management Science, Marketing Science and the Journal of Marketing Research, and Co-Editor of the Journal of Quantitative Marketing and Economics. I was a Co-Editor of the recent National Bureau of Economic Research volume on the Economics of Digitization. I received a National Science Foundation CAREER Award, which is the National Science Foundation’s most prestigious award in support of junior faculty who “exemplify the role of teacher-scholars through outstanding research, excellent education and the integration of education and research within the context of the mission of their organizations.”² I also received the Landau Prize for my work on the economics of payment platforms. I have testified twice before Congress on policy issues relating to new digital technologies and have presented my research to the Federal Trade Commission, the IMF, the Federal Communications Commission, and the OECD. I have published multiple academic papers in leading scientific, economics, marketing,

¹ “Platform Strategy: Building and Thriving in a Vibrant Ecosystem,” *MIT Management Executive Education*, available at <http://executive.mit.edu/openenrollment/program/platform-strategy-building-and-thriving-in-a-vibrant-ecosystem/>.

² For more information on the Faculty Early Career Development (CAREER) Program, see “Faculty Early Career Development Program,” *National Science Foundation*, available at https://www.nsf.gov/funding/pgm_summ.jsp?pims_id=503214.

management, and information systems journals, including *Science*, *Journal of Political Economy*, *RAND Journal of Economics*, *Management Science*, and *Information Systems Research*.

4. I am being compensated for my services in this matter at my customary hourly rate. In working on this report, I have been assisted by certain employees of Analysis Group, who provided support and assistance to me while preparing it. Analysis Group is being compensated for their time in this matter at their customary hourly rates. As an expert who is affiliated with the Analysis Group, I receive a proportion of their total billing.

II. CASE BACKGROUND, ASSIGNMENT, AND CONCLUSIONS

A. Case Background

5. In August 2018, the New York City Council enacted a law requiring the Taxi and Limousine Commission (“TLC”) to “establish a method for determining the minimum payment that must be made to a for-hire vehicle driver for a trip dispatched by a high-volume for-hire service.”³ In December 2018, the TLC voted to adopt a “minimum pay standard” for drivers of for-hire vehicles (“FHV’s”), which is scheduled to go into effect on February 1, 2019.⁴
6. The rule establishes a specific formula for the minimum amount per trip that FHV bases dispatching on average 10,000 or more trips per day must pay to drivers.⁵ The formula varies depending on whether the trip involves a wheelchair-accessible vehicle (“WAV”), and whether the trip involves a “shared ride.”⁶ The formula is a function of the distance and duration of the trip,

³ “Int. No. 890-B For-Hire Vehicle Driver Wage,” *New York City Council* (2018).

⁴ “Driver Pay,” *New York City Taxi & Limousine Commission*, available at http://www.nyc.gov/html/tlc/html/industry/driver_pay.shtml; “Int. No. 890-B For-Hire Vehicle Driver Wage,” 2018.

⁵ “Notice of Promulgation,” *New York City Taxi and Limousine Commission* (2018), p. 4.

⁶ “Notice of Promulgation,” 2018, p. 4. In a shared ride, multiple riders can be picked up and dropped off at different places sharing the same car. See, e.g., “UberPool vs. UberX - How Does UberPool Work?,” *Uber*, available at <https://www.uber.com/en-GH/ride/uberpool/> and “About Shared rides,” *Lyft Help*, available at <https://help.lyft.com/hc/en-us/articles/115013078848-About-Shared-rides>.

as well as the ridesharing platform’s “utilization rate.”⁷ For a non-WAV trip that is not shared, the current formula is:⁸

$$\text{Per Trip Driver Minimum Pay} = \frac{\$0.631 \times \text{Trip Miles} + \$0.287 \times \text{Trip Minutes}}{\text{Platform-Specific Utilization Rate}}$$

7. In this report, I will refer to the rule adopted by the TLC as the “Minimum Payment Rule,” and the application of the rule at a per trip level as the “Per Trip Calculation Requirement.”
8. A *Shared Ride Bonus*, which depends on the number of rider pickups, is added to any shared ride.⁹ That bonus will be determined by the TLC “after analyzing driver pay and expenses for shared rides and the occupancy rates for vehicles performing shared rides.”¹⁰
9. As motivation and justification for the Minimum Payment Rule, the TLC cites a report authored by James A. Parrott and Michael Reich, which studies the FHV industry and arrives at certain conclusions regarding the likely effects of the new policy.¹¹ In particular, Parrott and Reich conclude that “the TLC policy would correct some of the inefficiencies and inequities in the app industry by ensuring that driver expenses are covered, incentivizing improved driver utilization, rewarding drivers when they provide shared rides, and reducing growth in the number of new app-based drivers.”¹² Parrott and Reich, with Jason Rochford and Xingxing Yang, issued a revision to

⁷ A ridesharing platform’s utilization rate “is calculated by dividing the total amount of time drivers spend transporting riders on trips dispatched by the base [platform] by the total amount of time drivers are available to accept dispatches from the base [platform]” (“Notice of Promulgation,” 2018, p. 2). More generally, utilization is defined as “the percentage of a driver’s on-duty time that is spent with a passenger in their car” (“Notice of Promulgation,” 2018, p. 4). For the purposes of this report, I refer to the former, aggregate measure of utilization for a platform as the “platform-specific utilization rate,” and I use the terms “utilization” or “utilization rate” to refer to the general notion of utilization for an individual driver or group of drivers.

⁸ “Notice of Promulgation,” 2018, p. 3. For a WAV trip that is not shared, in the current formula, *Trip Miles* is multiplied by \$0.818 rather than \$0.613, to account for the increase in costs of providing wheel-chair accessibility. For the purposes of this report, I focus my discussion on the non-WAV formula. However, as the two formulas are based on similar premises, my discussion and conclusions apply equally to the WAV formula.

⁹ “Notice of Promulgation,” 2018, p. 4.

¹⁰ “Notice of Promulgation,” 2018, p. 4.

¹¹ Parrott, James A. and Michael Reich, *An Earnings Standard for New York City’s App-based Drivers: Economic Analysis and Policy Assessment*, The New School Center for New York City Affairs, July 2018 (“Parrott and Reich Report”). I refer to this as the Parrott and Reich Report or the Report in the rest of this document.

¹² Parrott and Reich Report, p. 5.

their report in January 2019, more than a month after the TLC adopted the minimum pay standard, reflecting (1) updated estimates of driver expenses and earnings, (2) an updated estimate of the increase in weekly and yearly drivers' payment stemming from the Per Trip Calculation Requirement of the Minimum Payment Rule, and (3) an updated analysis of the effect of the minimum pay standard.¹³

B. Assignment

10. I have been asked by counsel for Lyft to:

- a) Evaluate the Report from July 2018 by James A. Parrott and Michael Reich entitled "An Earnings Standard for New York City's App-based Drivers: Economic Analysis and Policy Assessment" and the Supplementary Report by James A. Parrott, Michael Reich, Jason Rochford, and Xingxing Yang from January 16, 2019, entitled "The New York City App-based Driver Pay Standard: Revised Estimates for the New Pay Requirement";
- b) Evaluate the economic merits of the Per Trip Calculation Requirement of the Minimum Payment Rule; and
- c) Evaluate the economic merits of using a platform-specific utilization rate in the Minimum Payment Rule.

C. Summary of Conclusions

11. I have reached the following conclusions:

i. The Parrott and Reich Report is Unreliable

12. The Parrott and Reich Report is not based on sound economic methodology and fails to assess the effect of the Minimum Payment Rule and the Per Trip Calculation Requirement. Therefore, it is

¹³ Parrott, James A. et al., *The New York City App-based Driver Pay Standard: Revised Estimates for the New Pay Requirement*, The New School Center for New York City Affairs, January 2019 ("Parrott and Reich Supplementary Report"). I refer to this as the Parrott and Reich Supplementary Report or the Supplementary Report in the rest of this document.

not useful for evaluating whether the Per Trip Minimum Payment Rule will be helpful or harmful from a public policy perspective. See Section IV.

13. The Report is based on erroneous estimates of driver gross earnings, hours, and expenses, therefore undermining the numerical inputs of the Minimum Payment Rule and the results of Parrott and Reich's analyses. See Section IV.B.
14. Parrott and Reich's "simulation model," which purports to evaluate the effects of the proposed Minimum Payment Rule and the Per Trip Calculation Requirement, contains both conceptual and calculation errors which render it unreliable:
 - a) Parrott and Reich attempt to examine the effects of a policy that would uniformly increase average driver pay rather than the actual effects of the Per Trip Calculation Requirement of the Minimum Payment Rule. See Section IV.C.i.
 - b) Parrott and Reich assume, rather than estimate or predict, changes in key economic outcomes such as fare increases, ridesharing platforms' commission rates, and drivers' utilization rates. They provide no economic basis for these assumptions, despite the fact that the relevant policy question — that is, what will happen to drivers' gross earnings — depends critically on what assumptions are made. See Section IV.C.ii.
 - c) Parrott and Reich's "simulation" ignores the basic economic necessity that the number of trips supplied by drivers must equal the number of trips demanded by riders. They effectively assume that drivers will supply (and be paid for) trips that no rider will take. See Section IV.C.iv.
 - d) Parrott and Reich assume without basis that utilization will increase, but fail to recognize the logical implication of this assumption for their model, namely that drivers will drive fewer hours. See Section IV.C.v.
 - e) Parrott and Reich's Supplementary Report fails to address these flaws, and the fact that the revised results are substantially different from the original results underscores the unreliability of the analyses. See Section IV.C.vi.

ii. Parrott and Reich’s Own “Simulation,” Correcting for Certain Miscalculations and Conceptual Errors, Predicts That the Minimum Payment Rule Will Decrease Driver Gross Earnings

15. One of Parrott and Reich’s own “simulations” (Scenario G) predicts that the Minimum Payment Rule and the Per Trip Calculation Requirement will lead to a steep rise in rider fares, fewer trips, and a slight *decrease* in driver gross earnings. They dismiss this potential outcome as “unlikely,” despite the fact that it is the one most closely aligned with ridesharing platforms’ incentive to pass through cost increases into fares. See Section IV.C.iii.
16. Parrott and Reich assume without basis that ridesharing platforms will voluntarily decrease their commission rates by half or more. They ignore the fact that 45 percent of drivers use multiple platforms, creating competition for drivers which leads to competitive pressure on the commission rate. If ridesharing platforms do not decrease their commission rates, or do so only modestly, Parrott and Reich’s “simulation” suggests that drivers’ gross earnings will decrease. See Section IV.D.
17. Having to correct Parrott and Reich’s “simulation model” for (i) choosing a profit maximizing scenario, (ii) the fact that the number of trips supplied must equal the number of trips demanded, and (iii) their assumed increase in driver utilization, underscores the lack of reliability of the Report. After these corrections, scenarios that Parrott and Reich deemed “plausible” in their July 2018 Report predict either that drivers’ gross earnings will decrease or, using the 20.7 percent increase in average driver pay derived in the Supplementary Report, that ridesharing platforms will charge *negative* commissions (i.e., ridesharing platforms will lose money on each ride). See Sections IV.C.v-vi.

iii. The Per Trip Calculation Requirement of the Minimum Payment Rule Does Not Make Economic Sense

18. There is no economic rationale for the Per Trip Calculation Requirement of the Minimum Payment Rule. In their analysis of driver pay, both reports state their key findings in terms of hourly or weekly earnings. Neither report evaluates the effects of the Minimum Payment Rule and the Per Trip Calculation Requirement directly. In their Supplementary Report, the authors analyze a uniform increase in “weekly aggregate gross pay” rather than a per trip simulation of how the Per Trip Calculation Requirement would affect the market. See Section V.A.

19. A Per Trip Calculation Requirement likely overshoots the objective set by the Minimum Payment Requirement. A Per Week Calculation of the Minimum Payment Rule would still ensure that the objective is achieved, but it would do so for the average trip, not for each trip individually. In other words, while the TLC purported to pass a Minimum Payment Rule ensuring the Minimum Payment Requirement's objective, the Per Trip Calculation Requirement of the Minimum Payment Rule goes above the Minimum Payment Requirement. See Section V.A.iii.

iv. The Per Trip Calculation Requirement of the Minimum Payment Rule Is Likely To Create Distortions That Will Hurt Drivers and Riders

20. The Per Trip Calculation Requirement of the Minimum Payment Rule will disproportionately affect driver payments for certain types of trips, and will likely increase congestion in some areas and generate longer rider wait times. Compared to Lyft's current payment structure, I find that the Minimum Payment Rule results in the highest increase in incentives for trips in the most congested areas: for these trips, pay increases up to 60 percent, or four-fold what Parrott and Reich themselves consider necessary. See Section V.B.i.
21. The Per Trip Calculation Requirement of the Minimum Payment Rule is likely to decrease the number of trips taken by riders more than necessary, as it is likely to disproportionately affect more price sensitive riders. See Section V.B.ii.
22. A Per Week Calculation gives ridesharing platforms the flexibility to find the least disruptive way of changing driver payments and rider fares to cover the cost of the Minimum Payment Requirement and would result in fewer distortions, benefiting drivers and riders alike. See Section V.B.iv.

v. Relying on Platform-Specific Utilization Rates May Have the Unintended Effect of Reducing Competition - See Section VI

23. The most obvious implication of the requirement that individual platforms' utilization be used to calculate a platform-specific floor for driver pay is that platforms with lower average driver utilization will have higher per trip costs.
24. The Minimum Payment Rule could entrench large incumbents by ensuring that their smaller rivals have higher per trip costs, harming competition. Parrott and Reich's failure to grapple with this

important policy issue further demonstrates the unreliability of their conclusion that the policy “incentivizes driver utilization.”

25. Less competition between platforms may be detrimental to drivers. With less competition, ridesharing platforms will be less likely to compete for drivers by offering lower commission rates or fewer innovative driver-friendly features.
26. With less competition, ridesharing platforms will be less likely to compete for riders. Fewer riders and a reduction in the demand for trips will result in reduced earnings for drivers.
27. The use of a platform-specific utilization rate has the potential to create a vicious cycle, whereby the Minimum Payment Rule will further increase for the small competitors and decrease for the large competitors. This would result in the growth of the largest competitors to the detriment of the smallest competitors, increasing market concentration.

III. INDUSTRY BACKGROUND

A. The Economics of Platforms and the Sharing Economy

28. A crucial shift in the economy over the past decade is the emergence of a variety of digital platforms, including ridesharing platforms, that help producers and consumers use resources better. This shift has been referred to as the “sharing economy,” reflecting the idea that digital platforms can ensure better use of resources through the automation of matching of buyers to sellers.
29. Ridesharing platforms provide an app-based platform that allows drivers and riders to efficiently coordinate trips. These digital platforms benefit both those who supply and those who demand the underlying services. In the context of ridesharing, platforms such as Lyft or Uber enable drivers to identify nearby potential riders more easily and quickly than was possible prior to the existence of these platforms. Likewise, riders can more easily and quickly signal their trip needs to nearby drivers.

30. Such platforms are characterized by network effects.¹⁴ Network effects occur when a platform becomes more valuable the more users it has. In the case of ridesharing platforms, riders find a platform more valuable the more drivers there are because they are more likely to be quickly matched with a driver, and drivers find a platform more valuable because there are more riders and their likelihood of finding a nearby rider is greater. The presence of network effects, means that pricing on a platform has to reflect incremental strategic considerations that are not faced by other businesses.
31. When I teach how to price a platform strategy, I highlight the notion of the three Es of designing a platform pricing structure, which are “Equilibrium, Enticement, and Evolution.”¹⁵ I emphasize that in addition to a platform using its pricing to maximize profits, its pricing structure (that is, the format in which it pays people, or charges people) has to achieve three other objectives:
- a) Equilibrium: Ensure that the pricing structure provides incentives so that at any one time there are enough users on both sides of the platform: For example, ensuring there are enough drivers to provide trips to riders on a Saturday night.
 - b) Enticement: Ensure that the pricing structure is flexible enough to ensure that the platform can entice new or marginal users. This might include setting up incentive schemes to entice new riders or entice drivers to test out a platform.
 - c) Evolution: Ensure that the pricing structure evolves seamlessly and also can adjust appropriately to shifts in competition.
32. As I highlight in this report, the Per Trip Calculation Requirement of the Minimum Payment Rule distorts these objectives to the detriment of both drivers and riders.
33. Ridesharing platforms do not restrict the number of riders requesting rides, nor do they force drivers to be on the road or off the road at any given time.¹⁶ Therefore, the primary mechanism

¹⁴ Tucker, Catherine, “Network Effects and Market Power: What Have We Learned in the Last Decade?,” *Antitrust*, Vol. 32, No. 2 (2018).

¹⁵ “Platform Strategy: Building and Thriving in a Vibrant Ecosystem,” *MIT Management Executive Education*, <http://executive.mit.edu/openenrollment/program/platform-strategy-building-and-thriving-in-a-vibrant-ecosystem/>.

¹⁶ Parrott and Reich Report, p. 47.

used to balance supply and demand is price. During times of high demand relative to supply, platforms will increase riders' fares and drivers' pay in order to incentivize riders to ride less and drivers to drive more. This is how a ridesharing platform achieves "Equilibrium."

34. Ridesharing platforms also face competition in acquiring both riders and drivers. Therefore, they may offer incentives to new riders to join the platform or to encourage existing riders to try new services. For example, they may offer incentives to riders to take shared rides by making shared rides relatively cheaper compared to solo rides.¹⁷ Such actions are all examples of "Enticement."
35. Ridesharing platforms have in general a flexible pricing structure which allows them to compete effectively while ensuring no unexpected fluctuations for drivers and riders. In exchange for providing a marketplace through which drivers and riders can efficiently transact, the platforms charge a commission to drivers, and sometimes riders.¹⁸ It is essential for platforms to maintain the flexibility of their pricing structures to be able to continue to compete and optimize their pricing to reflect the needs of their users. Such flexibility is an example of "Evolution."
36. The issue of competition is important, because as I have discussed in my research, the fact that both drivers and riders can and do easily use multiple apps means that there are strong competitive pressures in this industry.¹⁹ The ease with which drivers and riders can migrate across platforms ensures that platforms compete with one another by trying to provide the best possible experience for both drivers and riders. This competition takes place along a variety of dimensions including providing the fairest and most informative system of ratings for drivers and riders, providing background checks, improving algorithms to most efficiently match drivers to riders, and

¹⁷ For example, Lyft also unveiled their Triple Match program which had potential to reduce Lyft Line fares below the cost of public transportation in San Francisco. See Buhr, Sarah, "Lyft Line Gets Into Perpetual Ride Territory With Triple Match Service," *TechCrunch*, July 29, 2015. Lyft's website also advertises Lyft Line as offering shared trips at prices up to 60% less than original Lyft. See "Introducing Lyft Line, Your Daily Ride," *Lyft Blog* (August 6, 2014), <https://blog.lyft.com/posts/introducing-lyft-line>. Furthermore, Uber introduced Express Pool trips offering lower fares to riders willing to walk short distances. See Bhuiyan, Johana, "Uber's new 'Express Pool' is all about getting more riders to share rides," *recode*, February 21, 2018.

¹⁸ Maverick, J.B., "How Does Uber Make Money?," *Investopedia* (December 18, 2017), <https://www.investopedia.com/ask/answers/013015/how-do-ridesharing-companies-uber-make-money.asp>. See also "A Closer Look At Lyft's Valuation," *Forbes*, October 10, 2018 ("While most of the revenues go to the driver, [Lyft] usually generates 20% in net revenues per ride.").

¹⁹ Tucker, "Network Effects and Market Power: What Have We Learned in the Last Decade?," *Antitrust*, Vol. 32, No. 2 (2018).

introducing new types of rider experiences, such as shared or XL rides. There is also price competition for riders and drivers over fares, commission levels, and payments for joining that platform.

B. The Market for App-Based For-Hire Vehicles in New York City

37. The “high-volume” FHV services identified by the TLC are Uber, Lyft, Gett/Juno, and Via.²⁰ Parrott and Reich report that “app-based drivers now complete over 17 million trips in the city each month, double the number of medallion trips.”²¹ Uber has the highest share among these four ridesharing platforms, though that share has decreased in recent years due to competition.²² In Q1 2018, Lyft had a share close to 20 percent (growing from below 3 percent in Q2 2015), while Juno and Via collectively had just under 15 percent share.²³

IV. THE PARROTT AND REICH REPORT IS UNRELIABLE

38. The Parrott and Reich Report and Supplementary Report are not based on sound economic methodology, and they fail to reliably assess the likely effects of the Minimum Payment Rule and its Per Trip Calculation Requirement. Therefore, the Parrott and Reich Report is not helpful for evaluating whether the Minimum Payment Rule and the Per Trip Calculation Requirement will be helpful or harmful from a public policy perspective.
39. In addition to being uninformative about the likely effects of the Minimum Payment Rule and the Per Trip Calculation Requirement, the Report contains fundamental mistakes that lead Parrott and Reich to reach erroneous conclusions. I have identified three categories of mistakes: 1) mistakes in the data and assumptions Parrott and Reich use to estimate driver expenses, earnings, and hours; 2) mistakes in how Parrott and Reich execute their “simulation;” and 3) mistakes in assumptions underlying their “simulation.” In Section IV.A, I first provide an overview of the Parrott and Reich

²⁰ “Notice of Promulgation,” 2018, p. 1.

²¹ Parrott and Reich Report, p. 6.

²² Parrott and Reich Report, Exhibit 18.

²³ Parrott and Reich Report, Exhibit 18.

Report and Supplementary Report. I then provide further details of each category of mistakes in Sections IV.B-D.

A. Overview of Parrott and Reich Report

40. Parrott and Reich set out “to evaluate and provide feedback on [the TLC’s] proposed policy and to analyze the likely effects.”²⁴ To do so, they conduct two sets of analyses.

- a) Parrott and Reich attempt to estimate drivers’ hours, earnings, and expenses. These estimates are used to evaluate whether drivers’ earnings meet the Minimum Payment Requirement and serve as inputs to the Minimum Payment Rule.²⁵
- b) Parrott and Reich attempt to quantify how drivers, riders, and ridesharing platforms will adjust to the TLC’s proposed Minimum Payment Rule, using a series of alternative scenarios.

i. Measuring Driver Hours, Expenses, and Hourly Earnings

a. Driver hours and utilization rate

41. Parrott and Reich estimate a driver’s actual hours as the duration between the beginning of her first trip and the end of her last trip in a given “shift.”²⁶ They argue that their estimate is consistent with other statistical agencies’ measures because driver hours should include time spent on breaks and waiting time for customers to arrive.²⁷ They also claim that their measure of driver hours is underestimated since it does not include commuting to and from home.²⁸
42. Parrott and Reich start by calculating hours for drivers that only drive for one ridesharing platform (“single-platform drivers,” which represent 55 percent of the driver population as of October

²⁴ Parrott and Reich Report, p. 3.

²⁵ Parrott and Reich Report, p. 34.

²⁶ Parrott and Reich Report, p. 84. I do not have any opinions regarding the employment relationships between ridesharing platforms and drivers. Therefore, to the extent that the terminology used by Parrott and Reich implies an employment relationship, I paraphrase the terms used.

²⁷ Parrott and Reich Report, p. 22.

²⁸ Parrott and Reich Report, p. 22.

2017).²⁹ Using single-platform drivers' hours, they estimate the average utilization of each of the ridesharing platforms (Uber, Lyft, Gett/Juno, and Via).³⁰

43. This methodology cannot be used to calculate hours for drivers who use more than one platform, as their active hours on each platform effectively overlap. For instance, if a driver provides four trips in a day, the first and last through Lyft, and the second and third through Uber, her active hours on the Lyft and Uber platforms will overlap. Parrott and Reich therefore impute multi-platform drivers' hours for each of the ridesharing platforms used by the driver. Specifically, they calculate the total duration of trips driven for a specific platform, which they rescale by the platform-specific utilization for single-platform drivers only.³¹ The underlying assumption is that the utilization for multi-platform drivers is the same as those for single-platform drivers. I discuss this assumption in Section IV.B.iii.
44. Based on this methodology, Parrott and Reich estimate that, between June 2017 and October 2017, drivers' average and median hours were 33.3 hours and 32.5 hours per week, respectively.³² Using their estimation of driver hours and actual trip durations, Parrott and Reich estimate an average utilization rate of 58 percent.³³

b. Expenses

45. Parrott and Reich present an expense model that includes three categories of costs. The largest share of expenses associated with driving on a ridesharing platform are made up of operating costs, which include: monthly vehicle payments, commercial insurance, gas, vehicle maintenance, and

²⁹ Parrott and Reich Report, p. 21.

³⁰ Parrott and Reich Report, p. 21.

³¹ Parrott and Reich Report, p. 21. For instance, consider a driver who is active on multiple platforms. If that driver's trips with one ridesharing platform totaled 2 hours and this ridesharing platform's utilization for single-platform drivers were 50 percent, the imputed active time on that platform for the driver would be 4 hours (2/50 percent).

³² Parrott and Reich Report, p. 21.

³³ Parrott and Reich Report, p. 21.

vehicle cleaning.³⁴ Parrott and Reich find a total driver expense figure of 58.0 cents per mile (revised to 63.1 cents per mile in their Supplementary Report).³⁵

c. Hourly earnings

46. For each driver, Parrott and Reich aggregate the driver's payments across the four major ridesharing platforms, based on TLC's administrative earnings data collected for four weeks in 2016 and 2017.³⁶ In the Report, Parrott and Reich calculate average hourly earnings by dividing drivers' weekly earnings by their imputed estimates of driver hours.³⁷ In their Supplementary Report, they calculate average hourly and weekly earnings based on drivers' per-trip earnings.³⁸ They estimate that mean gross (before expenses) hourly earnings in mid-October 2017 were \$24.49 using the first method and \$23.42 using the second method.

ii. *The Minimum Payment Rule and the Per Trip Calculation Requirement*

47. Parrott and Reich discuss a Minimum Payment Rule consisting of a \$0.58 per-mile expense component (revised to \$0.631 in the Supplementary Report),³⁹ a \$0.287 per-minute factor, and a utilization rate which rescales the per-mile and per-minute components.⁴⁰ As they explain:
- a) "The **expense component** is intended to allow the typical driver to cover all the costs of acquiring and operating the vehicle (as well as the cost of licensing and training)."⁴¹

³⁴ Parrott and Reich Report, Exhibits 10A and 10B. The other two cost categories are one-time upfront administrative costs and recurring costs such as license renewal and periodic inspection. The costs in these categories are largely dictated by the TLC and/or the DMV, so I focus on ongoing vehicle acquisition and operating costs. See "Thinking About Driving an FHV? Costs and How Earnings Work for FHV Drivers," *New York City Taxi & Limousine Commission*, December 18, 2017, available at http://www.nyc.gov/html/tlc/downloads/pdf/thinking_about_driving_fhv.pdf.

³⁵ Parrott and Reich Report, p. 26 and Exhibit 10A and Parrott and Reich Supplementary Report, Exhibit 5.

³⁶ Parrott and Reich Report, pp. 23, 80.

³⁷ Parrott and Reich Report, Exhibit 9, p. 24.

³⁸ Parrott and Reich Supplementary Report, Exhibit 6, p. 5. Parrott and Reich do not explain what measure of hours they use to estimate average hourly pay.

³⁹ Parrott and Reich Supplementary Report, pp. 4–5. The per-mile expense component for WAVs was revised from \$0.804 to \$0.818 per mile.

⁴⁰ Parrott and Reich Report, Exhibit 15.

⁴¹ Parrott and Reich Report, p. 34 [emphasis added].

- b) “The \$0.287 **per minute factor** is intended to compensate drivers for their time at \$17.22 an hour (\$0.287 is \$17.22 divided by 60 minutes).”⁴²
- c) “In the case of the time factor, the **utilization rate** adjusts for the portion of each hour that a rider is not in the vehicle. In the case of the expense factor, the utilization factor adjusts for the expenses associated with pickup, cruising, and other non-passenger vehicle uses during the work shift.”^{43, 44}

48. Parrott and Reich also state that the “policy also includes a \$1 bonus per pickup for shared rides;” although, I understand that this \$1 bonus is not currently part of the TLC’s Minimum Payment Rule.
49. The Minimum Payment Rule requires that the minimum payment amounts be paid “for each trip dispatched by the Base” (this is the Per Trip Calculation Requirement), or on a per-hour basis.⁴⁵ Parrott and Reich describe the Per Trip Calculation Requirement in a footnote that explains that “[p]recisely, the pay standard formula” is applied to “[d]river minimum pay per trip.”⁴⁶ However, the main text of the Report specifies that the “precise means by which the pay standard will be implemented” has not been specified yet and that “[g]enerally, for a set time period (such as a week or a month), companies will evaluate each driver’s earnings using the total trip mileage and trip minutes for that company. If the compensation provided to a driver falls below the minimum pay standard, the companies will be required to make up the difference.”⁴⁷

iii. The Parrott and Reich “Simulation Model”

50. To address whether the proposed Minimum Payment Rule and the Per Trip Calculation Requirement will make drivers better off, Parrott and Reich purport to “examine through a

⁴² Parrott and Reich Report, p. 34 [emphasis added].

⁴³ Parrott and Reich Report, p. 35 [emphasis added].

⁴⁴ This rescaling assumes that drivers’ “non-passenger vehicle use” is the same as rider vehicle use. In particular, this assumes that drivers would drive as fast when cruising as when driving a rider.

⁴⁵ “Rulebook Chapter 59: For-Hire Service,” *New York City Taxi and Limousine Commission* (2014).

⁴⁶ Parrott and Reich Report, Footnote 35.

⁴⁷ Parrott and Reich Report, pp. 35–36.

simulation model how drivers, riders, and the app-based companies will react to the policy.”⁴⁸ In particular, their analysis seeks to predict how the Minimum Payment Rule and the Per Trip Calculation Requirement will affect several market outcomes of interest including: the change in drivers’ total earnings, changes in ridesharing platform commission rates, changes in rider fares, and changes in driver utilization. As I discuss in Section IV.C, Parrott and Reich’s approach assumes all economic outcomes of interest, rather than forecast them through economic modeling. Following the language of their report, I refer to their approach as a “simulation.”

51. Parrott and Reich revised their estimate of the effect of the Minimum Payment Rule and the Per Trip Calculation Requirement on drivers’ gross hourly earnings in their Supplementary Report; however, they do not appear to have updated their “simulation” approach.⁴⁹ In the remainder of this section, I focus on their “simulation” as outlined in their Report, but given that they have not addressed any of the flaws in their original “simulation,” the discussion here will apply equally to their revised estimates.
52. Parrott and Reich calculate that in order to increase drivers’ average net hourly earnings to the Minimum Payment Requirement of \$17.22, drivers’ average gross hourly earnings would need to increase by 13.2 percent.⁵⁰ They use this figure as their starting point for their “simulation.”⁵¹
53. Parrott and Reich then describe several “plausible scenarios,” the results of which depend on the assumptions made regarding how ridesharing platforms, drivers, and riders would react to the uniform increase in drivers’ hourly earnings.⁵² They construct three main “plausible scenarios” in which they assume — without evidence — that drivers’ hourly pay will increase by 13.2 percent,

⁴⁸ Parrott and Reich Report, p. 53. As I explain in Section IV.C, Parrott and Reich’s exercise is based on ad hoc scenarios rather than actual forecasting.

⁴⁹ Parrott and Reich present three new scenarios, which assume a 20.7 percent increase in gross hourly driver pay and increases in rider fares of 5, 8, and 10 percent. Parrott and Reich do not provide any other information on their assumptions; however, assuming these three new scenarios correspond to Scenarios A, B, and C from their original report, they would also assume a four percentage point increase in utilization rates, a 0.4 labor supply elasticity, and a -1.2 demand elasticity (Parrott and Reich Supplementary Report, p. 7; Parrott and Reich Report, Exhibit 20A).

⁵⁰ Parrott and Reich Report, p. 54. Parrott and Reich recently revised this 13.2 percent to 20.7 percent (Parrott and Reich Supplementary Report, p. 5.).

⁵¹ Parrott and Reich Report, Exhibit 20A.

⁵² Parrott and Reich Report, p. 59.

drivers' average utilization rate will increase by four percentage points, and rider fares will either remain the same, increase by 3 percent, or increase by 5 percent.⁵³ Importantly, these assumptions are imposed by Parrott and Reich, not derived through economic modelling.

54. In each of these “plausible” scenarios,⁵⁴ Parrott and Reich use a measure of labor supply elasticity of drivers to forecast changes in the number of driver hours.⁵⁵ Labor supply elasticity describes the degree to which drivers will increase or decrease the hours they drive as earnings increase or decrease. They base this estimate of labor supply elasticity on an unpublished paper by Horton et al.^{56, 57} Similarly, they use a demand elasticity for riders to project the decrease in riders' demand for trips in the face of the implied price increase.⁵⁸ The demand-elasticity for riders is the degree to which riders will demand more or less ridesharing services as price increases or decreases.
55. Parrott and Reich also attempt to calculate how rider wait time would be affected by the change in utilization and the shift in the ridesharing platforms' commission rate that would rationalize the assumed change in fares and the calculated change in rider demand.⁵⁹
56. Parrott and Reich note that their “three most important results” regard “the company commission rate; the change in passenger wait times; and the share of the cost of the pay increase absorbed by

⁵³ They also present what they call “alternative” scenarios, which assume an increase in the price of trips of 3 percent for Scenarios D, E, and F, and of 10 percent for Scenario G (Parrott and Reich Report, Exhibit 20A).

⁵⁴ Parrott and Reich Report, Exhibits 20A and 20B.

⁵⁵ Notably, the labor supply elasticity does not influence the results of Parrott and Reich's “simulation.” In their *ad hoc* scenarios, riders demand fewer trips than drivers supply. Even if drivers are willing to provide 5 percent or 10 percent more trips, this will not matter given that riders' demand for trips has declined.

⁵⁶ Parrott and Reich Report, p. 49 and Hall, Jonathan V., John J. Horton, and Daniel T. Knoepfle, “Labor Market Equilibrium: Evidence from Uber,” (2017), p. 42.

⁵⁷ Notably, in another paper, Horton et al. find that an increase in driver trip pay has no long term effect on drivers' hourly earnings — the result of drivers being active for more hours, but completing fewer trips in each hour they are active. Hall, Jonathan V., John J. Horton, and Daniel T. Knoepfle, “Pricing Efficiently in Designed Markets: Evidence from Ride-Sharing,” (2018), Figures 6, 7, and 8.

⁵⁸ The demand elasticity is fixed in all scenarios considered by Parrott and Reich. In one scenario only, Parrott and Reich change the supply elasticity of labor. Since the supply elasticity of labor is not, despite Parrott and Reich's claims, a central input in the model, I do not focus on this scenario. Parrott and Reich Report, Exhibits 20A and 20B.

⁵⁹ Parrott and Reich Report, Exhibits 20A and 20B. Parrott and Reich incorrectly cite Cook et al. (2018) as their source for the effect of utilization on wait times. It appears their source was Hall, Horton, and Knoepfle (2018); but that paper states that “[f]or a 10% increase in the fare, median wait times fell by 6%,” not that a “10 percent increase in driver utilization rates would likely increase response times by six percent” (Hall et al., “Pricing Efficiently in Designed Markets: Evidence from Ride-Sharing,” 2018, p. 4; Parrott and Reich Report, p. 58).

increased utilization.”^{60,61} Those results vary across scenarios: Depending on the scenario, the “change in overall pay of incumbent drivers” varies between minus 0.4 and plus 13.2 percent, and the decrease in the ridesharing platform’s commission rate that corresponds to the assumed change in trip prices varies between 2.4 percentage points and 11 percentage points (equivalent to a decrease of 14 percent to 66 percent).⁶² After recently revising their estimate of drivers’ earnings, Parrott and Reich note that, to accommodate the policy, fares would need to increase by an additional 5 percentage points while commission rates would need to decline even further, by at least an additional 1.5 percentage points.⁶³

57. In the Report, Parrott and Reich claim that the Minimum Payment Rule will result in a total yearly driver pay increase of \$335 million and \$284 million for New York City drivers.⁶⁴ In their Supplementary Report, they now claim that the Minimum Payment Rule will increase the earnings of New York City drivers by \$626 million per year.⁶⁵
58. Next, I evaluate Parrott and Reich’s estimates of expenses, earnings, and hours, and show that they are unreliable. I then discuss their “simulation” model and demonstrate that it is unreliable, flawed, and based on inaccurate assumptions.

B. Parrott and Reich’s Estimates of Driver Expenses, Earnings, and Hours are Unreliable

59. In any modelling exercise, the results can only be as reliable as the inputs. In this section, I discuss how the inputs used by Parrott and Reich are flawed, calling into question the reliability of Parrott

⁶⁰ As I describe in Section IV.C, the latter two outcomes directly depend on the assumption made by Parrott and Reich that utilization will increase. The former crucially depends on the assumption made by Parrott and Reich as to the change in fares.

⁶¹ Parrott and Reich Report, p. 58.

⁶² The current average commission rate is 16.6 percent and the new commission rates vary between 5.6 and 14.2 percent. Parrott and Reich Report, Exhibits 20A and 20B.

⁶³ Parrott and Reich Supplementary Report, p. 7. Parrott and Reich previously considered commission rates of 5.6, 8.3, and 10.1 percent in their main Scenarios A, B, and C (corresponding to price increase of 0, 3, and 5 percent). Their main estimates now consider commission rates of 4.1, 6.8, and 8.5 percent and price increases of 5, 8, and 10 percent.

⁶⁴ Parrott and Reich do not explain how they arrive at their aggregate estimate of the increase in total driver pay. The number is presumably derived from one of their preferred modelling scenarios in Exhibit 20 (“According to our calculations in Section 5, total driver pay would increase annually by about \$335 million.”), but they do not explicitly note which scenario they use to calculate this number. Parrott and Reich Report, p. 70.

⁶⁵ Parrott and Reich Supplementary Report, p. 6.

and Reich’s results, both in the formulation of the Minimum Payment Rule and for their “simulations.”

i. Overstated Expenses

60. Expenses are a critical input for Parrott and Reich, both to calculate drivers’ net earnings and to establish the “expense component” used in the Minimum Payment Rule. However, Parrott and Reich appear to have overstated expenses in both reports, leading to an underestimate of drivers’ net earnings and an overestimate of the average per-mile expense, which directly inflates the expense component of the Minimum Payment Rule.
61. As I described in Section IV.A.i, Parrott and Reich estimate the expenses incurred by drivers to be 58 cents per mile in their Report and 63.1 cents per mile in their Supplementary Report.⁶⁶
62. Many academic studies and industry sources suggest that expenses are likely below the Parrott and Reich estimates. Three academic studies, cited by Parrott and Reich, find significantly lower expenses, ranging between 25 and 36 cents per mile.⁶⁷ Additionally, *The Rideshare Guide*, containing information on how to succeed as a driver and written by the popular blogger behind therideshareguy.com,⁶⁸ provides a range of 20 to 40 cents per mile, where the higher bound would correspond to a brand new SUV and the lower bound to a 2013 Prius.^{69,70} And while Parrott and Reich rely on the IRS allowance for business use (53.5 cents per mile for 2017, the year of Parrott and Reich’s data) to bolster their claim that 58 cents per mile is reasonable, *The Rideshare Guide*

⁶⁶ Parrott and Reich Report, p. 24. Parrott and Reich Supplementary Report, p.4.

⁶⁷ Parrott and Reich Report, p. 33.

⁶⁸ As of January 2019, therideshareguy.com garnered over half a million page views per month. “About the Rideshare Guy: Harry Campbell,” *The Rideshare Guide*, available at <https://therideshareguy.com/about-the-rideshare-guy/>. Parrott and Reich also describe him as a “prominent blogger on the app driving industry.” Parrott and Reich Report, p. 80.

⁶⁹ Wisniewski, Mary, “‘The Rideshare Guy’ offers tips to Uber, Lyft drivers,” *Chicago Tribune*, May 21, 2018. Harry Campbell also conducts an annual survey of drivers, as acknowledged by Parrott and Reich (Parrott and Reich Report, p. 80 (“Harry Campbell (“The Rideshare Guy”), conducts an annual survey of drivers”)).

⁷⁰ Campbell, Harry, *The Rideshare Guide: Everything You Need to Know about Driving for Uber, Lyft, and Other Ridesharing Companies* (Skyhorse Publishing, 2018), pp. 107–108.

explains that “the actual cost to own and operate your vehicle is not 53.5 cents per mile...Your actual cost should be a whole lot less.”⁷¹

63. Parrott and Reich admit that their estimate of expenses is “considerably higher” than these sources, but they attribute this difference to New York City-specific factors that are not accounted for in those studies.⁷² However, New York City-specific factors are not the only reason that their estimate is high. Here I discuss one reason for the discrepancy between Parrott and Reich’s reports and other studies: their estimate of the monthly vehicle payment.
64. The vehicle payment is by far the largest contributor to Parrott and Reich’s expense estimate. They estimate vehicle payments to be \$9,609 per year, or 27.5 cents per mile.⁷³ This estimate, which falls in the middle of the range of estimates for the *entire* cost of operating a vehicle cited in the *Rideshare Guide*, is a weighted average of (a) estimated monthly lease payments, and (b) estimated monthly vehicle financing costs. While monthly lease payments are self-reported by drivers in a survey, Parrott and Reich estimate monthly vehicle financing costs themselves.
65. Parrott and Reich estimate monthly vehicle financing costs by reporting average manufacturer’s suggested retail prices (MSRPs) for different categories of vehicles, adding an 8.875 percent sales and use tax to those prices, and then estimating a monthly financing cost assuming a 60-month loan term and a 6.74 percent interest rate.⁷⁴ They do not explain where they obtained their estimates of MSRPs for different categories of vehicles, or which vehicles those estimates are based on.

⁷¹ Campbell, *The Rideshare Guide* (2018), p. 117.

⁷² Such factors include regulatory requirements of the TLC and potentially higher insurance costs. Parrott and Reich Report, p. 33.

⁷³ 27.5 cents per mile represents approximately 44 percent of the total estimated cost of 63.1 percent.

⁷⁴ Parrott and Reich Supplementary Report, p. 2.

Exhibit 1
Comparison of MSRP to Fair Purchase Price⁷⁵

	Parrott and Reich Avg. MSRP	Top Selling Make/Model	MSRP	Fair Purchase Price
Sedan	\$27,955	Toyota Camry	\$24,765	\$22,778
Luxury Sedan	\$61,135	Mercedes-Benz C-Class	\$41,245	\$37,615
Regular SUV	\$35,297	Jeep Grand Cherokee	\$35,490	\$33,939
Luxury SUV	\$46,690	Lexus RX	\$45,995	\$42,706
Compact	\$21,719	Honda Civic	\$21,145	\$19,360
Van	\$33,534	Honda Odyssey	\$31,085	\$28,781

Note: MSRP and Fair Purchase Price are based off Kelley Blue Book’s estimates for the basic model of the top selling make and model I identified for each vehicle type. Kelley Blue Book’s estimates for Fair Purchase Price are specific to New York City’s zip code 10001. Here, I assumed drivers were purchasing the newest model available on the market (2019 or 2018).

66. It is common knowledge that MSRPs are higher than actual sales prices for new cars.⁷⁶ In **Exhibit 1**, I report MSRPs for the top selling make and model in each of the categories used by Parrott and Reich, as well as the “fair purchase price” for New York City reported by vehicle valuation company Kelley Blue Book.⁷⁷ As expected, MSRP is higher than the fair purchase price in all

⁷⁵ Parrott and Reich Report, p. 25; Parrott and Reich Supplementary Report, p. 2; “AAA’s Your Driving Costs,” AAA, available at <https://exchange.aaa.com/automotive/driving-costs/#.XEuvnFxKhaQ.XEn23oWcFaT>; Wardlaw, Christian, “10 Most Popular Luxury Cars,” *JD Power*, September 24, 2016; “Most Popular SUVs of 2018: 2018 Jeep Grand Cherokee,” *Kelley Blue Book*, available at <https://www.kbb.com/most-popular-cars/suv/2018/?slide=4>; Chee, Brian, “Top 10 List: These are the best-selling luxury SUVs in America,” *NY Daily News*, March 7, 2018; Wardlaw, Christian, “10 Most Popular Small Cars,” *JD Power* (September 9, 2016), <https://www.jdpower.com/cars/sedans/10-most-popular-small-cars>; “New 2019 Toyota Camry L,” *Kelley Blue Book*, available at <https://www.kbb.com/toyota/camry/2019/l/?vehicleid=438938&intent=buy-new&category=sedan1/25>; “New 2018 Mercedes-Benz C-Class C 300,” *Kelley Blue Book*, available at <https://www.kbb.com/mercedes-benz/c-class/2018/c-300/?vehicleid=430426&intent=buy-new&category=sedan>; “New 2019 Jeep Grand Cherokee Laredo,” *Kelley Blue Book*, available at <https://www.kbb.com/jeep/grand-cherokee/2019/laredo/?vehicleid=439014&intent=buy-new&category=suv>; “New 2019 Lexus RX RX 350,” *Kelley Blue Book*, available at <https://www.kbb.com/lexus/rx/2019/rx-350/?vehicleid=439234&intent=buy-new&category=suv>; “New 2019 Honda Civic LX,” *Kelley Blue Book*, available at <https://www.kbb.com/honda/civic/2019/lx/?vehicleid=438955&intent=buy-new&category=sedan>; “New 2019 Honda Odyssey LX,” *Kelley Blue Book*, available at <https://www.kbb.com/honda/odyssey/2019/lx/?vehicleid=436086&intent=buy-new&category=van%2fminivan>.

⁷⁶ See, e.g., Morton, Fiona Scott, Jorge Silva-Risso, and Florian Zettelmeyer, “What matters in a price negotiation: Evidence from the U.S. auto retailing industry,” *Quantitative Marketing and Economics*, Vol. 9, No. 4 (2011).

⁷⁷ “About Us,” *Kelley Blue Book*, available at <https://www.kbb.com/company/about-us/> (“Kelley Blue Book is a vehicle valuation and automotive research company that provides reports on market value prices for new and used vehicles.”); Kelley Blue Book’s “fair purchase price” is based on actual transactions and is adjusted for

cases. On average, **Exhibit 1** shows that Parrott and Reich’s use of MSRP would overstate the price of a new vehicle by more than 8 percent compared to the fair purchase price — a measure of the prices that buyers actually pay. This means that Parrott and Reich use an overly high cost of vehicles in their vehicle financing calculations, meaning that the proposed cost estimate in the Minimum payment rule overshoots its objective of fulfilling the Minimum Payment Requirement. Using the fair purchase price reflecting actual prices paid for vehicles, the estimated vehicle payment costs would decline by more than five percent.⁷⁸

67. Parrott and Reich also assume that all drivers purchase brand new vehicles for business purposes. Ridesharing platforms do not require that drivers purchase or lease a new vehicle; assuming that all drivers would do so is unreasonable (in New York City, the TLC does not place any restriction on vehicle age).⁷⁹ In **Exhibit 2**, I report the average “fair purchase price” estimated by Kelley Blue Book for new and used vehicles in each of the categories used by Parrott and Reich. I find that the monthly weighted average financing costs for new and used vehicles is \$574 and \$369, respectively. These numbers are well below both the \$635 reported by Parrott and Reich in July,⁸⁰ and the combined \$803 per month financing/lease cost reported by Parrott and Reich in January.⁸¹ This means that Parrott and Reich overstate vehicle purchase expenses, and therefore the proposed cost estimate in the Minimum Payment Rule overshoots its objective of fulfilling the Minimum Payment Requirement. I find that using the monthly financing cost based on the fair purchase price for new vehicles would lower Parrott and Reich’s per-mile expense to \$0.615, and for used vehicles, it would lead to a further decline to a \$0.585 per-mile expense.⁸²

geographical region and seasonal trends. It is what a buyer “can expect to pay for a new car” in their geographic area. See “Car Values,” *Kelley Blue Book*, available at <https://www.kbb.com/car-values/>.

⁷⁸ In their Supplementary Report, Parrott and Reich estimate average monthly financing costs based on average MSRP for the 43 percent of drivers who own their cars. The weighted average of these costs is \$679.44. Using the Fair Purchase Price rather than MSRP, the average monthly financing costs for these drivers would be \$573.58. The lower financing costs would reduce Parrott and Reich’s estimate of financing and lease costs from \$802.93 per month to \$757.41 per month: $(\$802.93 - 43\% \times (\$679.44 - \$573.58))$.

⁷⁹ “New York State Driver: Applicant Requirement Checklist,” *Lyft*, available at <https://www.lyft.com/driver-application-requirements/new-york-state>; “Rulebook Chapter 59: For-Hire Service,” 2014.

⁸⁰ Parrott and Reich Report, p. 25.

⁸¹ Parrott and Reich Supplementary Report, p. 3.

⁸² In their Supplementary Report, Parrott and Reich estimate average monthly financing costs of \$679.44 for drivers who own their cars. Using the Fair Purchase Price rather than MSRP, the average monthly financing

Exhibit 2 Vehicle Payment Estimation⁸³

	New		Used	
	Fair Purchase Price ^[1]	Monthly Financing Cost ^[2]	Fair Purchase Price	Monthly Financing Cost
Sedan	\$22,778	\$489	\$13,564	\$291
Luxury Sedan	\$37,615	\$806	\$22,626	\$485
Regular SUV	\$33,939	\$728	\$21,075	\$452
Luxury SUV	\$42,706	\$915	\$33,050	\$709
Compact	\$19,360	\$415	\$14,043	\$301
Van	\$28,781	\$617	\$17,921	\$384
Weighted Average^[3]	\$26,736	\$574	\$17,198	\$369

Notes:

[1] Purchase price is based on Kelley Blue Book's Fair Purchase Price for the basic model of the top selling make and model for each vehicle type. New Fair Purchase Prices assume drivers are purchasing the newest

costs for drivers who own their cars would be \$573.58 for new cars and \$368.90 for used cars. Since 43 percent of drivers own their car, the lower financing costs would reduce Parrott and Reich's estimate of financing and lease costs from their current estimate of \$802.93 per month to \$757.41 per month: $(\$802.93 - 43\% \times (\$679.44 - \$573.58))$; or \$669.40 per month for used cars. Assuming drivers drive 35,000 miles per year, this would lead to a reduction in per-mile cost of \$0.016 for new cars and \$0.046 for used cars:

$$((\$757.41 - \$802.93) \times \frac{12 \text{ months}}{35,000 \text{ miles}} = -\$0.016).$$

⁸³ Parrott and Reich Report, p. 25; Parrott and Reich Supplementary Report, pp. 2–3; “AAA’s Your Driving Costs,” AAA, <https://exchange.aaa.com/automotive/driving-costs/#.XEuvnFxKhaQ.XEn23oWcFaT>; Wardlaw, “10 Most Popular Luxury Cars,” *JD Power*, September 24, 2016; “Most Popular SUVs of 2018: 2018 Jeep Grand Cherokee,” *Kelley Blue Book*, <https://www.kbb.com/most-popular-cars/suv/2018/?slide=4>; Chee, “Top 10 List: These are the best-selling luxury SUVs in America,” *NY Daily News*, March 7, 2018; “Auto Loan Calculator,” *Bank of America*, available at <https://www.bankofamerica.com/auto-loans/auto-loan-calculator/>; Wardlaw, “10 Most Popular Small Cars,” September 9, 2016; “New 2019 Toyota Camry L,” *Kelley Blue Book*, <https://www.kbb.com/toyota/camry/2019/l/?vehicleid=438938&intent=buy-new&category=sedan1/25>; “Used 2016 Toyota Camry LE Sedan 4D,” *Kelley Blue Book*, available at <https://www.kbb.com/toyota/camry/2016/le-sedan-4d/?intent=buy-used&mileage=44711&pricetype=retail&condition=good&persistedcondition=good>; “New 2018 Mercedes-Benz C-Class C 300,” *Kelley Blue Book*, <https://www.kbb.com/mercedes-benz/c-class/2018/c-300/?vehicleid=430426&intent=buy-new&category=sedan>; “Used 2016 Mercedes-Benz C-Class C 300 Sedan 4D,” *Kelley Blue Book*, available at <https://www.kbb.com/mercedes-benz/c-class/2016/c-300-sedan-4d/?intent=buy-used&mileage=44118&pricetype=retail&condition=good&persistedcondition=good>; “New 2019 Jeep Grand Cherokee Laredo,” *Kelley Blue Book*, <https://www.kbb.com/jeep/grand-cherokee/2019/laredo/?vehicleid=439014&intent=buy-new&category=suv>; “Used 2016 Jeep Grand Cherokee Laredo E Sport Utility 4D,” *Kelley Blue Book*, available at <https://www.kbb.com/jeep/grand-cherokee/2016/laredo-e-sport-utility-4d/?vehicleid=415725&intent=buy-used&category=suv&mileage=46556&pricetype=retail&condition=good>; “New 2019 Lexus RX RX 350,” *Kelley Blue Book*, <https://www.kbb.com/lexus/rx/2019/rx-350/?vehicleid=439234&intent=buy-new&category=suv>; “Used 2016 Lexus RX RX 350 Sport Utility 4D,” *Kelley Blue Book*, available at

model available on the market (2019 or 2018). Used Fair Purchase Prices assume drivers are purchasing the 2016 model.

[2] Monthly payments are based on the same assumptions made by Parrott and Reich in their Supplementary Report: zero down payment, 60 monthly payments, 8.875% sales tax, and a 6.74 interest rate. Consistent with Parrott and Reich, Bank of America's auto loan calculator was used to estimate monthly financing costs.

[3] In Exhibit 2 of their Supplementary Report, Parrott and Reich estimate the share of app-based trips for each vehicle type. These shares are used to calculate the weighted average.

68. Parrott and Reich also include payments for very expensive luxury vehicles, such as luxury SUVs and luxury sedans, which would be eligible for premium fares. These high-end vehicles qualify drivers to drive for the app-based equivalent of black car service, such as UberBlack or Lyft Lux, and offer opportunities for drivers to earn more.⁸⁴ For example, a driver with a luxury vehicle who uses the Lyft platform may earn three to five times more than a driver with a standard vehicle who uses the Lyft platform.⁸⁵ It is unlikely that these premium fares fall below the Minimum Payment Rule. Therefore, Parrott and Reich's estimate of monthly vehicle payments, which serves as an input into the Minimum Payment Rule, includes high monthly payments on luxury vehicles which are likely not driven by drivers that would be affected by the Minimum Payment Rule. This again leads them to overstate the expense component in the Minimum Payment Rule, which means its overshoots its objective of fulfilling the Minimum Payment Requirement. If one were to exclude these luxury vehicles from Parrott and Reich's vehicle payment estimation and use the fair

<https://www.kbb.com/lexus/rx/2016/rx-350-sport-utility-4d/?intent=buy-used&mileage=44711&pricetype=retail&condition=good&persistedcondition=good>; "New 2019 Honda Civic LX," *Kelley Blue Book*, <https://www.kbb.com/honda/civic/2019/lx/?vehicleid=438955&intent=buy-new&category=sedan>; "Used 2016 Honda Civic LX Sedan 4D," *Kelley Blue Book*, available at <https://www.kbb.com/honda/civic/2016/lx-sedan-4d/?intent=buy-used&mileage=44118&pricetype=retail&condition=good&persistedcondition=good>; "New 2019 Honda Odyssey LX," *Kelley Blue Book*, <https://www.kbb.com/honda/odyssey/2019/lx/?vehicleid=436086&intent=buy-new&category=van%2fminivan>; "Used 2016 Honda Odyssey LX Minivan," *Kelley Blue Book*, available at <https://www.kbb.com/honda/odyssey/2016/lx-minivan-4d/?intent=buy-used&mileage=48266&pricetype=retail&condition=good&persistedcondition=good>.

⁸⁴ "Lyft Lux, Lux Black, and Lux Black XL rides for drivers," *Lyft*, available at <https://help.lyft.com/hc/en-us/articles/115012923147-Lyft-Lux-Lux-Black-and-Lux-Black-XL-rides-for-drivers#aboutabout>;

"UberBLACK: High-end rides with professional drivers," available at <https://www.uber.com/ride/uberblack/>.

⁸⁵ "Elevate Your Earnings With Lyft Lux and Lyft Lux SUV," *Lyft: The Hub* (May 25, 2017), <https://thehub.lyft.com/blog/lux>.

purchase price, per-mile expenses would be reduced from \$0.631 to \$0.606 for new vehicles and \$0.576 for used vehicles.⁸⁶

ii. Understated Earnings

69. Parrott and Reich estimate drivers' gross earnings as an input into their net earnings calculation. However, they do not include all sources of earnings in their estimation of driver pay. First, they ignore tips in their earning calculations. Tips represent 5.4 percent of gross driver pay for drivers who use the Lyft platform, and a smaller share for other ridesharing platforms. Tips appear to be increasing by 7 or 8 percent each year.⁸⁷ Uber followed Lyft by allowing in-app tipping in 2017, and Lyft recently introduced a feature allowing riders to set an automatic tip percentage to be added to the trip fare on all trips.⁸⁸
70. Second, it is unclear whether they include Uber's information on incentives payments and Via's promotions information, the two ridesharing platforms for which the data was available.⁸⁹ While their gross earnings estimate does not serve as a direct input into the Minimum Payment Rule, the "per minute factor" of \$0.287 is intended to compensate drivers at the Minimum Payment Requirement of \$17.22 per hour. However, this factor ignores the fact that not all driver compensation is paid on a per trip basis. In fact, ridesharing platforms routinely use bonus payments to incentivize drivers to supply trips during certain hours. By not accounting for these

⁸⁶ In their Supplementary Report, Parrott and Reich estimate average monthly financing costs of \$679.44 for drivers who own their cars. Using the Fair Purchase Price rather than MSRP and excluding "Luxury Sedan" and "Luxury SUV", the average monthly financing costs for drivers who own their cars would be \$511.14 for new cars and \$309.09 for used cars. Since 43 percent of drivers own their car, the lower financing costs would reduce Parrott and Reich's estimate of financing and lease costs from their current estimate of \$802.93 per month to \$730.56 per month: $(\$802.93 - 43\% \times (\$679.44 - \$511.14))$; or \$643.68 per month for used cars. Assuming drivers drive 35,000 miles per year, this would lead to a reduction in per-mile cost of \$0.025 for new cars and \$0.055 for used cars: $((\$730.56 - \$802.93) \times \frac{12 \text{ months}}{35,000 \text{ miles}} = -\$0.025)$.

⁸⁷ Dickey, Megan Rose, "Uber Drivers Made More Than \$600 Million in Tips in One Year," *TechCrunch*, June 21, 2018.

⁸⁸ Vincent, James, "Lyft adds driver-friendly features including default tipping option," *The Verge*, November 15, 2018.

⁸⁹ Parrott and Reich Report, pp. 80–81. Parrott and Reich calculate gross driver pay based on driver payment minus tolls. It is not clear whether Uber's data on incentives payments and Via's promotion data were incorporated into the driver payment.

payments when calculating the “per minute factor” corresponding to \$17.22 per hour, Parrott and Reich necessarily overshoot the intended objective of the Minimum Payment Requirement.

71. Take, for example, a full-time (40 hours in a week) driver who earns \$200 in weekly bonuses. Those bonuses add \$5 per hour to the driver’s effective pay. In order to earn an average of \$17.22 per hour during the week, that driver would need to earn \$12.22 per hour, net of expenses, from her per-trip compensation. Even assuming that the other inputs into the Minimum Payment Rule, such as drivers’ average utilization rate and expenses of 63.1 cents per mile, were correctly calculated, the correct “per minute factor” for this driver would be \$0.204, not \$0.287.
72. This problem with Parrott and Reich’s analysis, derives from the Per Trip Calculation Requirement of the Minimum Payment Rule, which requires application of the minimum pay formula on a per-trip basis despite the fact that not all driver compensation is paid on a per-trip basis.

iii. Overstated Driver Hours

73. The methodology used by Parrott and Reich to calculate driver hours suffers from multiple shortcomings that likely overestimate driver hours. Overestimates of driver hours lead to underestimates of drivers’ utilization, which lead to underestimates of hourly earnings. If the TLC uses the same measure in the Minimum Payment Rule, a deflated utilization would also inflate the payment floor under the Minimum Payment Rule; that is, ridesharing platforms like Lyft would be required to pay more than is necessary to achieve the stated policy goal of \$17.22 per hour due to the incorrect calculation of utilization.
74. Parrott and Reich calculate driver active hours as the time difference between the first pickup time and the last drop-off time. While Parrott and Reich argue that drivers’ active hours should account for breaks, they include “breaks” of up to three hours in their calculations.⁹⁰ This means that a driver that drives before and after a big sporting event or a concert, taking a “break” during the length of the event, would be counted as having driven during the duration of the event. However, in most industries, working time does not include very long breaks in the middle of the day,⁹¹

⁹⁰ Parrott and Reich Report, p. 22.

⁹¹ Parrott and Reich include “breaks” that can last up to three hours. Parrott and Reich Report, p. 81.

particularly for workers paid on an hourly basis.⁹² Parrott and Reich also claim that their measure of driver hours is underestimated since it does not include commuting to and from home. However, time spent commuting is also typically not included in working time, so Parrott and Reich’s claims of a conservative underestimate are incorrect.⁹³

75. Consider a driver who drives on the Lyft platform between the hours of 8:00 AM and 11:00 AM, and signs back on to Lyft from 2:00 PM to 7:00 PM, but takes an additional hour and a half to run errands for herself between the hours of 2:00 PM to 7:00 PM. Parrott and Reich would consider her active hours to have lasted 11 hours, even though she was only available to drive on Lyft for 6.5 hours. If she spent 4 of those hours on Lyft-dispatched trips, Parrott and Reich would estimate that her utilization was 36 percent, while her actual utilization was 62 percent.
76. Second, while Parrott and Reich rely on the utilization of single-platform drivers to impute driver hours for multi-platform drivers, drivers classified as single-platform drivers may also drive for other companies, such as food or grocery delivery companies.⁹⁴ As driving times for those companies are not available to Parrott and Reich, Parrott and Reich may incorrectly classify drivers as single-platform drivers, which would overstate their estimate of hours.⁹⁵
77. Last, Parrott and Reich impute, rather than observe, the driver hours for multi-platform drivers, a population that makes up 45 percent of all drivers.⁹⁶ Central to their imputation is the assumption that the utilization for multi-platform drivers is the same as for single-platform drivers. While Parrott and Reich justify this assumption based on the fact that “[t]he TLC reports that utilization is similar for one-app and two-app drivers,” such a claim is surprising because a driver who uses

⁹² “Wage and Hour Division (WHD),” *United States Department of Labor*, July 2008, available at <https://www.dol.gov/whd/regs/compliance/whdfs22.htm>. Moreover, it is likely that many drivers are in fact active on a ridesharing platform during their “commute.”

⁹³ “Travel Time,” *U.S. Department of Labor*, available at <https://www.dol.gov/general/topic/workhours/travelttime> (“Time spent in home-to-work travel by an employee in an employer-provided vehicle, or in activities performed by an employee that are incidental to the use of the vehicle for commuting, generally is not ‘hours worked’ and, therefore, does not have to be paid.”).

⁹⁴ *The Rideshare Guide* mentions the following examples of food and grocery delivery companies: DoorDash, Postmates, Caviar, GrubHub and Instacart. (Campbell, *The Rideshare Guide* (2018), p. 144.)

⁹⁵ Parrott and Reich Report, footnote 17.

⁹⁶ Parrott and Reich Report, p. 21.

multiple platforms is likely to get trips faster than a driver who only uses one platform.⁹⁷ Indeed, multiple technologies now exist for drivers to help facilitate precisely the process of obtaining trips across multiple platforms as quickly and as easily as possible.⁹⁸ These tools would tend to lead to higher driver utilization.

C. Parrott and Reich’s “Simulation Model” Is Unreliable and Flawed

78. In this section, I assess whether:

- Parrott and Reich’s “simulation” constitutes a reliable method for evaluating the Minimum Payment Rule and the Per Trip Calculation Requirement; and
- Parrott and Reich’s “simulation” accurately estimates the average effects of the Minimum Payment Rule and the Per Trip Calculation Requirement.

i. Parrott and Reich Take an Unsupportable Shortcut to Estimate the Effect of the Pay Standard

79. Parrott and Reich choose an unsupportable shortcut to evaluate the Minimum Payment Rule and the Per Trip Calculation Requirement. Despite endorsing a Rule on a *per trip* basis, they develop a “simulation” based on aggregate pay that is unable to account for the changes in incentives and market distortions that are specific to the per-trip formulation of the Rule.

80. The Minimum Payment Rule and the Per Trip Calculation Requirement would lead to large changes in driver pay for some trips while leaving pay for other trips unchanged. For example, the pay floor would affect certain trips during off-peak hours when demand is already low relative to supply, but would not affect trips during times of peak demand. As such, drivers’ hourly earnings will not be uniformly affected by the Per Trip Calculation requirement of the Minimum Payment Rule. As I discuss in Section V.B, Parrott and Reich’s use of a uniform change in drivers’ hourly pay overlooks critical market distortions that arise from the per-trip formulation of the Rule. Parrott and Reich’s shortcut approach casts doubt on whether their “simulation” is able to meaningfully

⁹⁷ Parrott and Reich Report, footnote 17.

⁹⁸ Katz, Miranda, “This App Lets Drivers Juggle Competing Uber and Lyft Rides,” *WIRED*, February 15, 2018.

account for effects and market distortions specific to the Per Trip Calculation Requirement of the Minimum Payment Rule.

ii. Parrott and Reich's "Simulation" Is Ad Hoc and Lacks Economic Support

81. In principle, an economist could combine an economic model of the industry with data on actual trips, payments, and fares, to simulate or forecast changes in economic outcomes that are likely to occur as drivers and platforms adjust to the new policy. Such a simulation should account for drivers' incentives (drivers may supply more rides when pay goes up), platforms' incentives (platforms would like to charge a commission which maximizes their own profits, subject to competition from rivals and the need to balance riders' demand with drivers' supply), and riders' incentives (riders will demand fewer rides when fares increase). Parrott and Reich did not conduct such an exercise. The changes in drivers' total earnings, platform commission rates, rider fares, and driver utilization that they report are not predictions generated by their model. Instead, they are assumptions imposed by Parrott and Reich themselves. Because Parrott and Reich effectively assume, rather than estimate, all economic outcomes of interest, their method is unreliable and cannot be used to predict the likely effects of the Minimum Payment Rule or the Per Trip Calculation Requirement.
82. In the seven fictional scenarios presented in the Report's "simulation," Parrott and Reich assume, rather than forecast, changes in rider fares and commissions that they deem "plausible."⁹⁹ They claim that the "most likely" response of ridesharing platforms to the 13.2 percent increase in hourly driver pay is to raise rider fares between 0 and 5 percent.¹⁰⁰ However, they make no attempt to explain why they consider these responses more "likely" than any other. Similarly, in their Supplementary Report, they claim, without basis, that a 20.7 percent aggregate pay increase would result in an increase in rider fares between 5 and 10 percent. Here, too, Parrott and Reich have no rationale for picking these figures. These assumptions are imposed by Parrott and Reich, not derived through economic modelling. Ridesharing platforms, like all firms, have an incentive to

⁹⁹ Parrott and Reich Report, p. 58.

¹⁰⁰ Parrott and Reich Report, p. 58.

maximize their profits.¹⁰¹ These platforms operate in a competitive industry and make strategic choices that balance increases in rider prices against the loss of riders when prices go up. Parrott and Reich do not attempt to analyze these strategic choices or their implications for the proposed Rule.

83. As a result, the change in price stemming from the proposed pay standard cannot be assumed, as Parrott and Reich have done, based on whether the increase seems “plausible” or “unlikely.”¹⁰² Rather, the change in price will be chosen by the ridesharing platforms as they react to the predicted increase in driver pay per trip, depending on how they expect riders to react to the fare increase. The total commissions received by ridesharing platforms in each of the scenarios depends on how much of the predicted 13.2 percent increase in hourly driver pay is shared with riders in the form of higher rider fares, which also affects the demand for trips.

iii. Parrott and Reich’s “Simulation” Does Not Consider Platforms’ Incentives

84. In economics, firms are typically modeled as profit-maximizing entities.¹⁰³ It is possible to apply this central tenet of economics to the scenarios considered by Parrott and Reich to evaluate which of their proposed scenarios results in the highest total commissions — that is, the product of rider fares and the commission rate — for ridesharing platforms, and is therefore most likely to occur given platforms’ incentive to maximize their profits.
85. In their seven scenarios (three “most likely” in Exhibit 20A and four alternative scenarios in Exhibit 20B), Parrott and Reich consider four different increases in rider fares of zero percent, three percent, five percent, and ten percent. Each of these scenarios assumes that ridesharing platforms will pass less than one hundred percent of the increase in driver pay through to consumers. In **Exhibit 3**, I calculate the total ridesharing platform commissions (in the upper panel) and the change in drivers’ gross earnings predicted by Parrott and Reich’s “simulation” for each of the assumed increases in rider fares (in the bottom panel). As I discuss in more detail in

¹⁰¹ Carlton, Dennis W. and Jeffrey M. Perloff, *Modern Industrial Organization*, 4 ed. (Pearson, 2005), p. 58 (“The objective of any firm, including a competitive firm, is to maximize its profits (or, equivalently, minimize its losses).”).

¹⁰² Parrott and Reich Report, pp. 58–60.

¹⁰³ Carlton and Perloff, *Modern Industrial Organization* (2005), p. 58.

Section IV.C.iv, the estimated effect on drivers' gross earnings that I present correctly account for the decline in trips as rider fares increase.

86. Of Parrott and Reich's three "most likely" scenarios, ridesharing platforms have the highest total commissions in Scenario C, corresponding to a five percent increase in fares. However, Parrott and Reich's alternative Scenario G, corresponding to a ten percent increase in fares, gives ridesharing platforms the highest total commissions among all scenarios they consider.¹⁰⁴ While this ten percent increase in rider fares results in the highest total commissions of the scenarios Parrott and Reich consider, it leaves both drivers and riders worse off, with a decrease in drivers' gross earnings of \$10 million and approximately 24 million fewer trips demanded each year.¹⁰⁵
87. While Parrott and Reich's Scenario G is the most in line with ride-sharing platforms' profit-maximizing incentives, they dismiss it as "unlikely" because it results in "several adverse consequences" including "eliminat[ing] the policy-related driver pay increase for all incumbent drivers."¹⁰⁶ In other words, Parrott and Reich claim without support that an increase in average fares of zero, three, or five percent is "likely," but conclude that an increase in fares of ten percent is "unlikely" solely because it does not permit an increase in drivers' gross earnings. Though Parrott and Reich dismiss it, their own "simulation" predicts that the most likely outcome of the Per Trip Minimum Payment Rule will be a steep rise in rider fares, a fall in available active hours for incumbent drivers, and no benefit to drivers in the form of higher earnings.

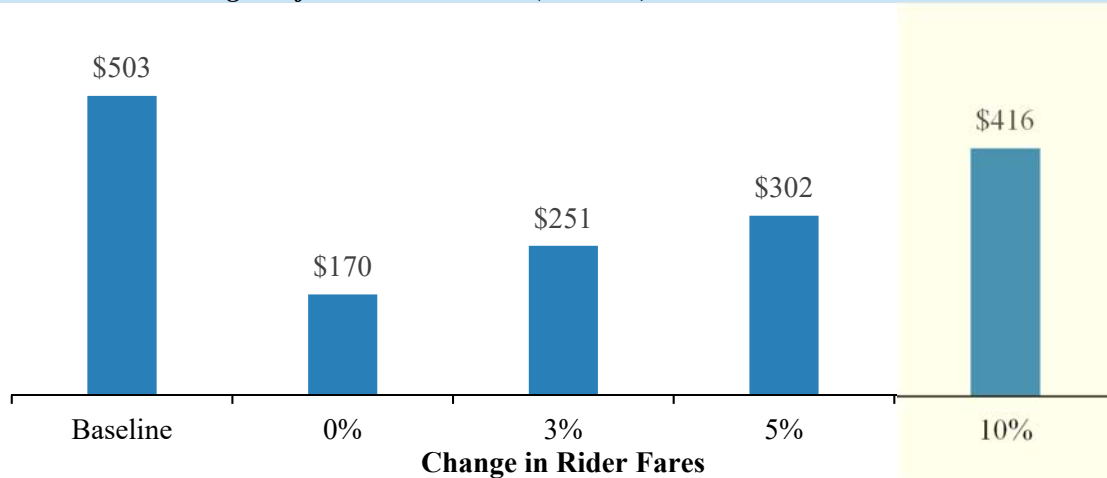
¹⁰⁴ As I discuss in Section IV.D.ii, there is no evidence that ridesharing platform commission rates are high nor that ridesharing platforms have room to further reduce commission rates.

¹⁰⁵ Parrott and Reich Report, Exhibit 20B. Parrott and Reich forecast that a 10 percent increase in rider fares will lead to a 12 percent decline in trips demanded. There were approximately 17 million dispatch trips in the NYC FHV market in February 2018 (Parrott and Reich Report, p. 6).

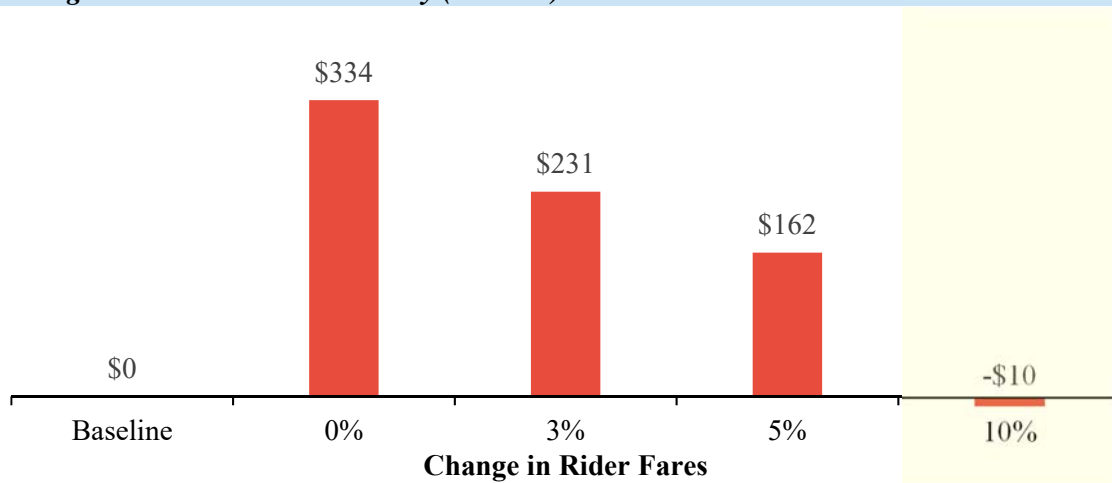
¹⁰⁶ Parrott and Reich Report, p. 61.

Exhibit 3
Effects of a 13.2 Percent Increase in Driver Gross Hourly Pay
According to Parrott and Reich’s “Simulation”¹⁰⁷

A. Annual Ridesharing Platform Commissions (millions)



B. Change in Annual Total Driver Pay (millions)



Notes:

- [1] Total ridesharing commissions are the difference between total industry revenue and total gross driver pay.
- [2] The change in total driver pay is calculated as the product of the change in driver gross hourly pay (13.2 percent) and the change in the quantity of trips demanded by riders. This amount, reflecting Parrott and Reich’s calculation of the “Percent change in overall pay of incumbent drivers,” does not account for the effect of changes in utilization.
- [3] The change in industry revenue is calculated as the product of the change in the price of rider fares and the change in the quantity of trips demanded by riders, where the change in the quantity of trips demanded is equal to the change in rider fares multiplied by -1.2, the elasticity of demand for trips used by Parrott and Reich.
- [4] Baseline gross driver pay can be calculated as the product of the number of drivers (61,111), average hourly earnings (\$24.49), average imputed weekly hours (32.5), and 52 weeks in a year (Parrott and Reich Report, Exhibits 11 and 12). Assuming a baseline commission rate of 16.6 percent, baseline industry revenue can be calculated as gross driver pay divided by (1 - 16.6 percent).

88. While Parrott and Reich’s Supplementary Report contains a higher estimate of the increase in average driver pay necessary to achieve the Minimum Payment Requirement, it contains minimal updates to their “simulation” analysis. Parrott and Reich consider increases in rider fares of five percent, eight percent, and ten percent in response to the 20.7 percent increase in aggregate driver pay.¹⁰⁸ As I show in **Exhibit 4**, of the three increases in rider fares considered, ridesharing platforms have the highest total commissions under the largest increase in rider fares (ten percent). While Parrott and Reich do not consider any alternative scenarios in their Supplementary Report, their own “simulation” suggests that an even larger increase in rider fares is the likely outcome. In the final bar of **Exhibit 4**, I show the effects predicted by Parrott and Reich’s “simulation” of a 15 percent increase in rider fares.¹⁰⁹ As in their original report, their own “simulation” predicts that the outcomes more aligned with ridesharing platforms’ profit-maximizing incentives would result in a large increase in rider fares and a decline in gross pay for incumbent drivers.

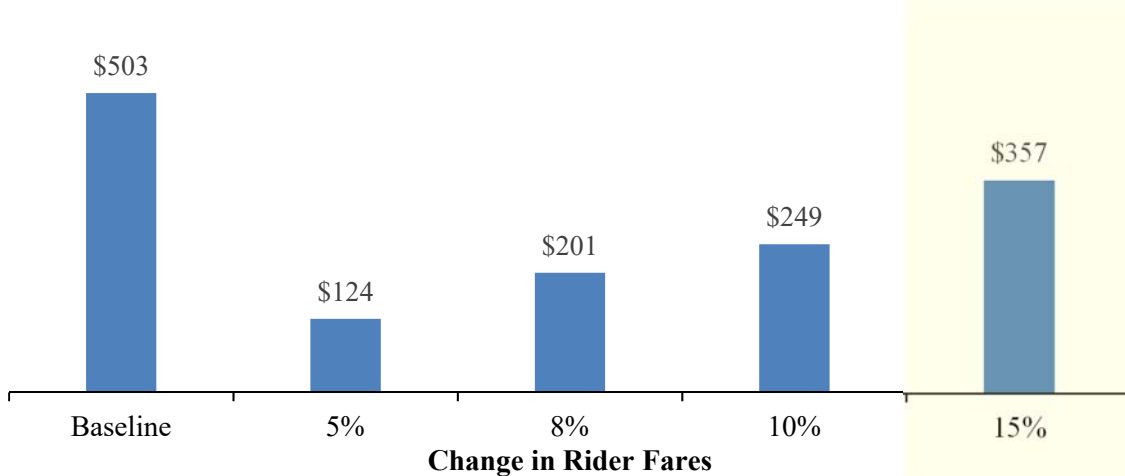
¹⁰⁷ Parrott and Reich Report.

¹⁰⁸ Parrott and Reich Supplementary Report, p. 7.

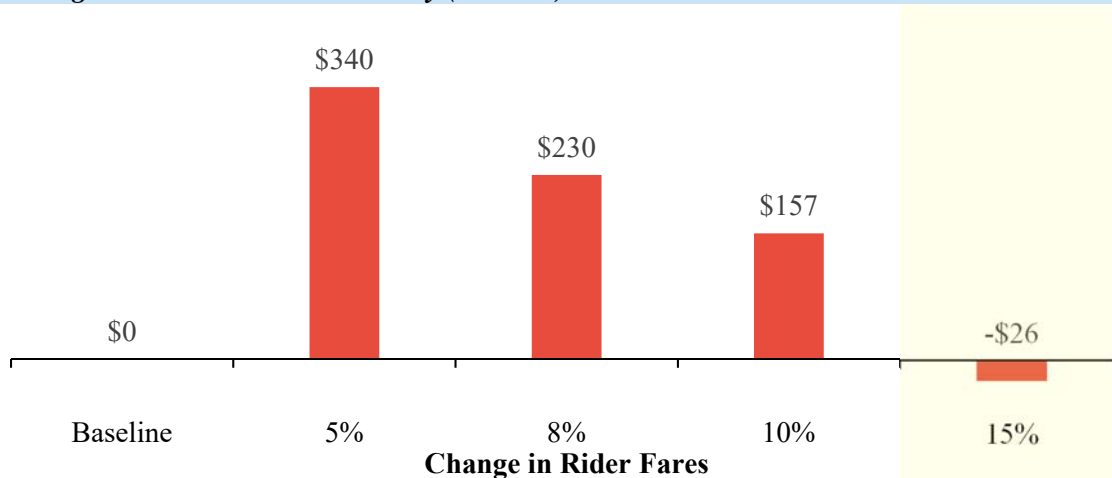
¹⁰⁹ A 15 percent increase in rider fares in response to a 20.7 percent increase in driver pay is roughly the same pass-through rate as a 10 percent increase in rider fares in response to a 13.2 percent increase in driver pay. Scenario G in their first report.

Exhibit 4
Effects of a 20.7 Percent Increase in Driver Gross Hourly Pay
According to Parrott and Reich’s “Simulation”¹¹⁰

A. Annual Ridesharing Platform Commissions (millions)



B. Change in Annual Total Driver Pay (millions)



Notes:

- [1] Total ridesharing commissions are the difference between total industry revenue and total gross driver pay.
- [2] The change in total driver pay is calculated as the product of the change in the gross driver hourly pay (20.7 percent) and the change in the quantity of trips demanded by riders. This amount, reflecting Parrott and Reich’s calculation of the “Percent change in overall pay of incumbent drivers,” does not account for the effect of changes in utilization.
- [3] The change in industry revenue is calculated as the product of the change in the price of rider fares and the change in the quantity of trips demanded by riders, where the change in the quantity of trips demanded is equal to the change in rider fares multiplied by -1.2, the elasticity of demand for trips used by Parrott and Reich.

¹¹⁰ Parrott and Reich Report; Parrott and Reich Supplementary Report.

- [4] For the purpose of comparison to Exhibit 3, the baseline gross driver pay (before expenses) is calculated as the product of the number of drivers (61,111), average hourly earnings (\$24.49), average imputed weekly hours (32.5), and 52 weeks in a year (Parrott and Reich Report, Exhibits 11 and 12). Assuming a baseline commission rate of 16.6 percent, baseline industry revenue can be calculated as gross driver pay divided by (1 - 16.6 percent).
- [5] The final scenario considers a 15 percent increase in rider fares. Such an increase would be similar to the 10 percent increase in rider fares Parrott and Reich had considered in response to the 13.2 percent increase in driver gross hourly pay.

iv. Parrott and Reich’s “Simulation” Does Not Adequately Account for Changes in Supply and Demand, Leading to Incorrect Results

89. Parrott and Reich’s “simulation” approach is also internally inconsistent. A core tenet of running a platform business, and of economics more generally, is the need to match supply and demand — this is the “Equilibrium” concept that I discussed in Section III.A. However, the *ad hoc* scenario method proposed by Parrott and Reich ignores the economic necessity that the number of trips supplied by drivers must be the same as the number of trips taken by riders.
90. In all of the scenarios that they consider, Parrott and Reich predict that “drivers are likely to increase their working hours” and provide “more trips per hour.”¹¹¹ Parrott and Reich attribute this increase in trips to the combination of an increase in pay and higher utilization. Yet, while they predict that drivers will provide more trips, they also claim that “if passenger fares rise, the consumer demand response is likely to **reduce** the number of trips demanded.”¹¹² This means that the number of trips supplied is greater than the number of trips demanded in their “simulation.” Such an outcome is not possible, and a model that predicts (or assumes) such an outcome is fundamentally flawed.
91. In **Exhibit 5**, I focus on Scenario G from Parrott and Reich’s report and demonstrate how their “simulation” fails to balance supply and demand. In Scenario G, Parrott and Reich assume that ridesharing platforms react to the 13.2 percent increase in gross hourly driver earnings by increasing rider fares by 10 percent and increasing the driver utilization rate from 58 percent to 62 percent.¹¹³ Parrott and Reich predict that the increase in hourly driver earnings will cause drivers

¹¹¹ Parrott and Reich Report, pp. 53, 61.

¹¹² Parrott and Reich Report, pp. 57, 61 [emphasis added]. See also rows 1 and 2 of Exhibits 20A and 20B and row 4 of Exhibits 20A and 20B.

¹¹³ Note that in Parrott and Reich’s Supplementary Report, they instead consider a 20.7 percent increase in drivers’ gross hourly pay (Parrott and Reich Supplementary Report, p. 5).

to increase their hours by 5.3 percent (row 7), and the increase in utilization will cause drivers to provide 6.9 percent more trips (row 8), leading to a 12.2 percent increase in trips supplied (row 9, highlighted).¹¹⁴

92. Next, Parrott and Reich *assume* that fares will rise 10 percent, and they predict that the fare increase will cause riders to demand 12.0 percent fewer trips (row 10, highlighted) in response to the increase in fares. Based on this, Parrott and Reich conclude that the “net change in trips” is 0.2 percent (row 11), the sum of the 12.2 percent increase in trips supplied and the 12.0 percent decline in trips demanded.
93. But that is not how supply and demand work. If drivers were willing to supply 12.2 percent more trips (as Parrott and Reich predict in row 9), those trips would not occur, as there is no rider demand for them. If there is less demand than supply, the quantity provided in the market will be driven by the demand. Conversely, if supply is lower than demand, the quantity provided in the market will be driven by the supply. To see this, imagine a world where, for a given level of drivers’ pay and riders’ fare, there are 20 persons who would like a trip but only 10 drivers willing to offer a trip. In that case, only 10 trips will occur. Similarly, in a world where there are only 10 persons who would like a trip but 20 drivers willing to offer a trip, only 10 trips will occur. Parrott and Reich, by contrast, would assume that all 20 trips would occur.¹¹⁵

¹¹⁴ Note that Parrott and Reich incorrectly calculate the “percent increase in trips provided by incumbent drivers” since they do not account for the higher utilization on the additional hours of incumbent drivers. The correct value is 12.5 percent ($1.053 \times 1.069 - 1$) rather than 12.2 percent.

¹¹⁵ Assuming that in the baseline supply is equal to demand at 10 trips provided, Parrott and Reich would calculate (1) the increase in trips provided by drivers as $(20-10)/10 = 100\%$ increase, and (2) the percent change in the demand for trips: $(10-10)/10 = 0\%$ change. Parrott and Reich would then calculate the net change in the number of trips as $100\% + 0\% = 100\%$; leading them to conclude that drivers supply 10 more trips.

Exhibit 5
Explanation of Parrott and Reich’s “Simulation”¹¹⁶
Scenario G

Assumptions

[1]	Change in Cost of Total Driver Pay	+13.2%
[2]	Utilization Rate (Baseline)	+58%
[3]	Utilization Rate (With Assumed Increase)	+62%
[4]	Change in Rider Fare	+10%
[5]	Labor Supply Elasticity	+0.40
[6]	Demand Elasticity for Rides	-1.20

Outcomes (according to Parrott and Reich)

[7]	Percent increase in hours of incumbent drivers in response to pay increase	$[1] \times [5]$	5.3%
[8]	Percent increase in trips provided by incumbent drivers as utilization increases	$([3] - [2]) / [2]$	6.9%
[9]	Percent increase in trips provided by incumbent drivers	$[7] + [8]$	12.2%
[10]	Percent change in demand for trips resulting from fare changes	$[4] \times [6]$	-12.0%
[11]	Net change in number of trips by incumbent drivers	$[9] + [10]$	0.2%
[12]	Percent change in overall pay of incumbent drivers after adjusting for effects of fare changes	$(1+[1]) \times (1+[10]) - 1$	-0.4%
[13]	Net percentage change in fare revenue, relative to no policy change	$(1+[4]) \times (1+[10]) - 1$	-3.2%
[14]	Ridesharing platform commission rate. Current = 16.6 percent	$1 - (1-0.166) \times (1+[12]) / (1+[13])$	14.2%
[15]	Change in rider median wait times	$[8] \times (6/10) \times 300$ seconds	12 seconds
[16]	Share of cost of pay increase absorbed by increased utilization rates	$[8] / [1]$	52%

Notes:

- [1] Parrott and Reich claim that gross driver hourly pay would need to increase by 13.2 percent to ensure that drivers are paid the minimum amount under the Minimum Payment Requirement.
- [2] Parrott and Reich do not provide an explanation of how they calculate the outcomes associated with the 13.2 percent increase in gross driver hourly pay. Where no explanation has been provided by Parrott and Reich, a calculation resulting in the same outcomes as Parrott and Reich has been included in this table.

94. It is illogical to “net out” changes in demand and supply, as Parrott and Reich do. This error on their part means that they overestimate how many trips drivers will be able to provide, and therefore how much drivers will earn under the proposed Minimum Payment Requirement. In their report, Parrott and Reich claim that the Minimum Payment Requirement will increase driver earnings by \$335 million per year. Parrott and Reich do not explain how they arrive at their estimate; however, it appears to be equal to a 13.2 percent increase in baseline gross driver pay.¹¹⁷ Such an assumption would assume no decline in ridesharing trips.
95. This estimate of the benefit to drivers ignores ridesharing platforms’ incentives, and it fails to account for the fact that supply must equal demand. Once these factors are accounted for, Parrott and Reich’s own “simulation” predicts that the Minimum Payment Rule will lead to a \$10 million decline in gross driver pay in Scenario G, the most likely of their scenarios to materialize, given platforms’ incentive to profit-maximize.¹¹⁸ In other words, Parrott and Reich’s estimate of the benefit to drivers overshoots by \$345 million. Even this reduced estimate, as I discuss in the Section IV.C.v, likely overstates the benefits of the proposed policy.

v. Parrott and Reich’s “Simulation” Incorrectly Accounts for Its Own Assumption on Utilization Improvement

96. Parrott and Reich claim that an increase in utilization “will provide the companies’ primary means of absorbing the effect of the pay standard” and suggest that it represents “the largest effect on the adjustment process.”¹¹⁹ Despite the centrality of utilization to their results, Parrott and Reich make algebraic errors in accounting for their own assumption of utilization improvement, which lead to overestimating the change in drivers’ earnings.

¹¹⁶ Parrott and Reich Report.

¹¹⁷ Parrott and Reich Report, p. 54. Baseline gross driver pay (before expenses) is equal to approximately \$2.5 billion. This can be calculated as the product of the number of drivers (61,111), average hourly earnings (\$24.49), average imputed weekly hours (32.5), and 52 weeks in a year (Parrott and Reich Report, Exhibits 11 and 12).

¹¹⁸ The 0.4 percent (\$10 million) decline in driver pay is calculated as the product of the 13.2 percent increase in drivers’ hourly payment and the 12.0 percent decline in the number of trips $(1+0.132) \times (1-0.120) - 1$.

¹¹⁹ Parrott and Reich Report, pp. 53, 57.

97. Utilization, which is defined as the share of an hour with a paying rider in the car, can be thought of as simply the number of trips per hour (assuming that the length of trips is fixed). If, from one day to the next, drivers complete more trips per hour, utilization goes up. Likewise, if, from one to the next, drivers complete the same number of trips in fewer hours, utilization also increases. Parrott and Reich’s “simulation” fails to account for this simple relationship.
98. As shown in **Exhibit 5**, Parrott and Reich mistakenly claim that the assumed utilization increase leads to an “increase in trips provided by incumbent drivers.”¹²⁰ It does not. Riders request fewer trips in their model, meaning that the only way utilization can go up in the face of a decrease in trips is if those trips are completed in fewer hours. Indeed, the 4 percentage point increase in utilization rates that Parrott and Reich assume in their rough calculation implies that the total hours that drivers are active would fall by more than six percent.¹²¹ If there is a fall in demand for trips as well as an increase in how many trips drivers can offer each hour, then the number of hours in total that drivers are active must fall more steeply than the drop in trip demand. Not only are there fewer trips to go around, but fewer hours are needed to complete the trips that remain. This decline in available trips has real economic consequences for drivers: it is equivalent to a decrease of 240,000 hours per week — tantamount to taking more than 10,000 app-based drivers off the road (assuming each driver is active for 32.5 hours each week).¹²²
99. Parrott and Reich claim to incorporate into their “simulation” the “effect on company costs of utilization adjustments by the companies.”¹²³ They acknowledge that increased utilization will lead to falling driver hours, and note that the only way that increased utilization will not lead to a

¹²⁰ Parrott and Reich Report Exhibit 20A, row 2.

¹²¹ The 6.9 percent increase in utilization would lead to a 6.5 percent decline in hours: $(\frac{1}{1+0.069} - 1 = -0.065)$. See Appendix C for a full derivation.

¹²² The 12 percent reduction in demand for trips (**Exhibit 5**, row 10) and the 6.9 percent increase in utilization (**Exhibit 5**, row 8) will lead to an 18 percent decline in driver hours, assuming the average trip length does not change, based on Parrott and Reich’s model $(\frac{1-0.12}{1+0.069} - 1 = -0.177)$. See Appendix C for a full derivation. Parrott and Reich estimate that total driver hours for the week of October 15, 2017 was 1,990,639 and average hours for each driver were 32.5. An 18 percent decline would reduce total hours by 351,893 hours, equivalent to the average weekly hours of 10,827 drivers.

¹²³ Parrott and Reich Report, p. 56.

“net reduction in driver hours [is] if there is substantial further market growth.”¹²⁴ Parrott and Reich do not appear to have any basis for suggesting there will be market growth. Indeed, in their report they note that previous growth is “not sustainable.”¹²⁵

100. Though drivers being active for fewer hours may be perceived as a benefit by some drivers, the rule is formulated with the idea that a certain number of hours are needed to cover the fixed costs of owning a vehicle. Therefore, the combination of a large decrease in earnings with a large decrease in hours may not achieve the goals of covering drivers’ fixed expenses, which are unrelated to the number of miles driven.
101. **Exhibit 6** reports the change in gross driver pay, as reported by Parrott and Reich, and the change in gross driver pay for Scenario G accounting for each of the corrections I have described.^{126,127} More details are provided in Appendix C. With these corrections, Parrott and Reich’s own “simulation” shows a decline in total driver gross earnings in Scenario G, indicating that their estimated benefit to drivers was off by more than half a billion dollars. Even Parrott and Reich’s Scenario C, which they describe as one of the “most likely,” predicts a decrease in drivers’ gross

¹²⁴ Parrott and Reich Report, p. 57.

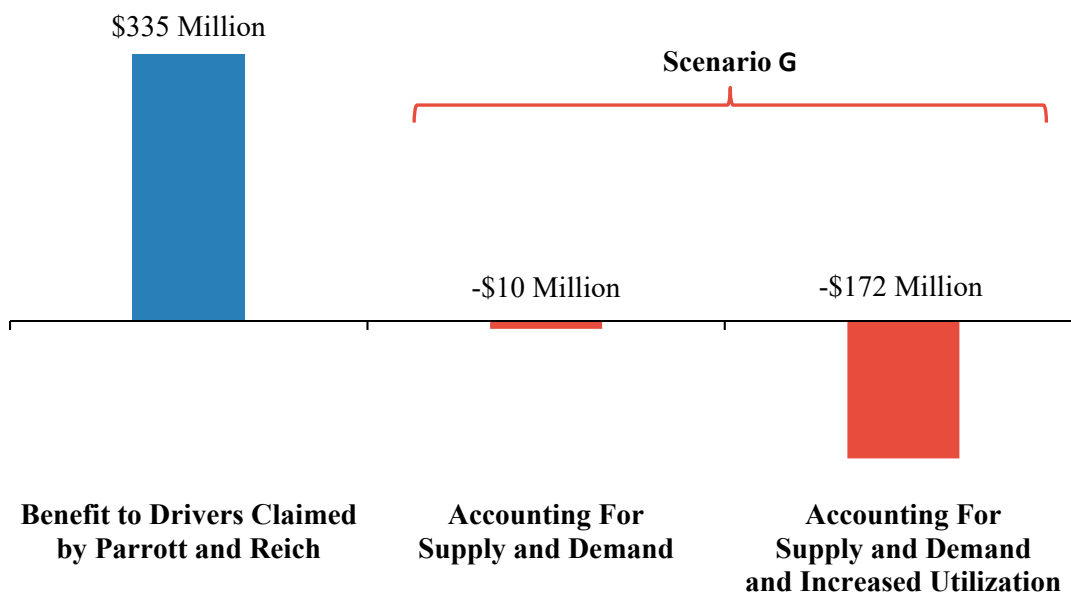
¹²⁵ Parrott and Reich Report, p. 50.

¹²⁶ While I focus on Scenario G here, I also find that gross driver pay declines in Scenario C, one of the scenarios that Parrott and Reich consider “most likely” to occur, once I account for supply and demand and the assumed increase in utilization.

¹²⁷ In the Report, Parrott and Reich’s forecast is based on a 14 percent increase in gross hourly earnings for drivers who made below \$17.22 per hour, which they translate into a 13.2 percent increase. See Parrott and Reich Report, p. 32 and Exhibit 20A. Throughout the Report, Parrott and Reich explain that the higher cost of driver pay will be absorbed by the increase in utilization (See, e.g., “Our simulations will show that increasing utilization will provide the companies’ primary means of absorbing the effect of the pay standard” and “Share of cost of pay increase absorbed by an increased utilization rate (6.9% efficiency gain divided by 13.2%)”). Parrott and Reich Report, p. 57 and Exhibit 20A. The underlying assumption is that some of the increase in hourly earnings would come from an increased number of trips per hour, which is a direct consequence of the higher utilization. Parrott and Reich’s “simulations” ignore the effect of this increased number of trips per hour. The direct consequence of the higher utilization rate is that each trip will need to be paid a lower rate. This will happen once the utilization rate used in the Minimum Payment Rule adjusts. In the short term, since the utilization rate used in the Minimum Payment Rule is fixed at 58 percent, if the utilization rate increases to 62 percent, drivers’ pay may increase by more than 13.2 percent hourly, until the change in utilization rate is updated and adequately reflected in the Minimum Payment Rule. This also highlights the potential distortions generated by the fixed quarterly platform-specific utilization rate used in the Minimum Payment Rule.

earnings once the mathematical relationship between driver hours and driver utilization is accounted for.¹²⁸

Exhibit 6
Change in Annual Gross Driver Pay¹²⁹



Notes:

- [1] Baseline gross driver pay (before expenses) can be calculated as the product of the number of drivers (61,111), average hourly earnings (\$24.49), average imputed weekly hours (32.5), and 52 weeks in a year.
- [2] The change in total driver pay is calculated as the product of the change in gross driver hourly pay (13.2 percent) and the change in the quantity of trips demanded by riders divided by the increased utilization of drivers.

vi. Parrott and Reich’s Recent Revisions Underscore the Unreliability of their “Simulation Model”

102. Parrott and Reich’s recent revisions to their estimates of the Per Trip Minimum Payment Requirement contemplate a different increase in average hourly pay for drivers — more than 50 percent higher than their previous estimate (20.7% instead of 13.2%). Rather than discussing the implications for their simulation model, they simply note that the higher increase in driver pay

¹²⁸ The change in total gross driver pay is calculated as the product of the change in gross driver hourly pay (13.2 percent) and the change in the quantity of trips demanded by riders (-6 percent) divided by the increased utilization of drivers (6.9 percent): $((1 + 0.132) \times \frac{1 - 0.06}{1 + 0.069}) = 1 - 0.005$.

¹²⁹ Parrott and Reich Report.

would now require reductions in ridesharing platform commission rates by as much as 26 percent more than previously thought to accommodate the policy.¹³⁰ Indeed, under the “most likely” increases in rider fares that Parrott and Reich considered in their original report — 0, 3, and 5 percent — their “simulation” would now forecast commission rates of -0.7, 2.3, and 4.1 percent.¹³¹ In other words, in one of the scenarios that Parrott and Reich considered to be the most “plausible,” ridesharing platforms would, on average, lose money on trips. Parrott and Reich now suggest that even larger increases in rider fares would be required to accommodate the policy, leading to a decline of as much as 2 million trips per month.¹³²

103. Parrott and Reich now claim that the Minimum Payment Rule will lead to an even larger increase in aggregate earnings for New York City drivers of “about \$626 million.”¹³³ Parrott and Reich note in their Supplementary report that for drivers with at least one trip below the Minimum Payment Rule, their mean gross trip pay on a weekly basis will increase by \$184.58.¹³⁴ They then aggregate this average increase across the 80,000 weekly drivers, 85 percent of whom are NYC residents, to arrive at their estimate of \$626 million.
104. Of note, Parrott and Reich’s calculation assumes that every driver is active for the same number of hours before and after the pay standard.¹³⁵ In other words, Parrott and Reich’s estimate of the benefit to drivers is not an outcome of their “simulation,” and does not account for the fare increases, demand decreases, and utilization increases that they assume will occur as a result of the policy.

¹³⁰ Parrott and Reich Supplementary Report, p. 7. Parrott and Reich previously considered commission rates of 5.6, 8.3, and 10.1 percent in their main Scenarios A, B, and C. Their main estimates now consider commission rates of 4.1, 6.8, and 8.5 percent. The decline in commission rates from 5.6 to 4.1 percent represents a 26.7 percent decline in the forecasted commission rate.

¹³¹ Parrott and Reich Report, p. 61. See **Exhibit 5** for a derivation of the commission rate in Parrott and Reich’s “simulation.”

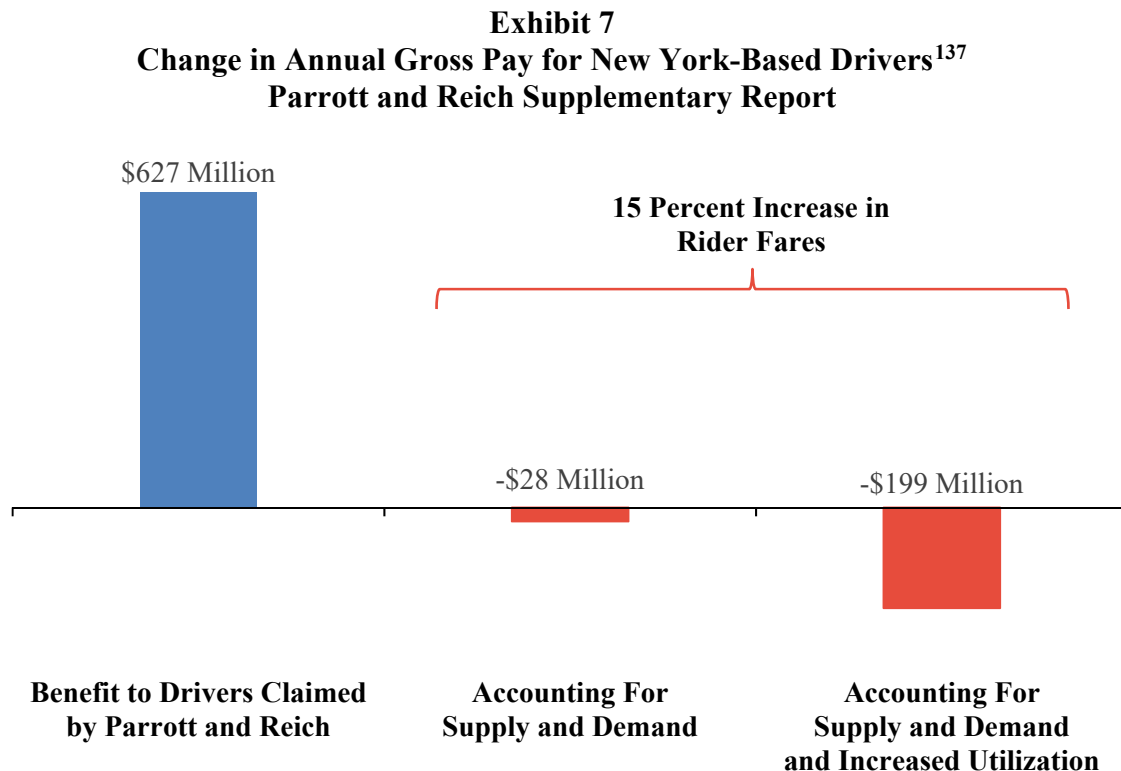
¹³² Parrott and Reich Report, Exhibit 20B. Parrott and Reich forecast that a 10 percent increase in rider fares will lead to a 12 percent decline in trips demanded. There were approximately 17 million app dispatch trips in the NYC FHV market in February 2018. See Parrott and Reich Report, p. 6.

¹³³ Parrott and Reich Supplementary Report, p. 6.

¹³⁴ Parrott and Reich Supplementary Report, Exhibit 7.

¹³⁵ Parrott and Reich Supplementary Report, Exhibit 7. Before the pay standard, Parrott and Reich calculate that, in their sample, drivers drive 31.95 hours per week (\$714.02/22.35). After the pay standard, Parrott and Reich calculate that, in their sample, drivers drive 32.25 hours per week (\$898.60/27.86).

105. Ultimately, Parrott and Reich’s *ad hoc* scenarios do not show that drivers’ gross earnings will be increased by the policy, even in their Supplementary report. As I show in **Exhibit 7**, Parrott and Reich’s claim that drivers’ aggregate earnings will increase by \$626 million, is considerably overstated. Assuming that ridesharing platforms will increase fares by 15 percent,¹³⁶ and correctly accounting for Parrott and Reich’s assumed increase in driver utilization, their “simulation” predicts that drivers’ gross earnings will decrease by almost \$200 million.



Notes:

- [1] In Parrott and Reich’s Supplementary Report, baseline gross pay is calculated as the product of the number of drivers (80,000), the share of drivers in New York (85%), the mean gross hourly pay for all trips in the week of October 16–22, 2017 (\$23.42), average imputed weekly hours (32.5), and 52 weeks in a year.
- [2] The change in total gross driver pay is calculated as the product of the change in gross driver hourly pay (20.7 percent) and the change in the quantity of trips demanded by riders divided by the increased utilization of drivers.

¹³⁶ An increase in fares of 15 percent represents pass-through of roughly three quarters of the assumed 20.7 increase in driver pay.

¹³⁷ Parrott and Reich Report; Parrott and Reich Supplementary Report.

D. Parrott and Reich’s “Simulation Model” Relies on Unsupported and Inaccurate Assumptions

106. The Parrott and Reich “simulation model” is also based on unsupported and inaccurate assumptions. Using such flawed and arbitrary assumptions renders their conclusions unreliable.

i. The Parrott and Reich Report Ignores the Effect of Multi-Homing Drivers

107. In platform economics, ridesharing is used as a canonical example of a platform service where “multi-homing” would be expected. The basic idea behind multi-homing is that it is cheap for both riders and drivers to use multiple platforms at the same time in order to get the best deal. For instance, if a rider trying to get a trip is quoted either substantial “prime” or “surge” pricing or a long wait for drivers in the Lyft app, it is virtually costless for her to open the Uber app and see whether it offers a more attractive option.¹³⁸ Further, various applications, such as Google Maps or Bellhop, allow riders to compare the price and wait times for multiple ridesharing apps.¹³⁹ Riders often use multiple ridesharing apps interchangeably.¹⁴⁰

108. Similarly, a driver not receiving the surge pricing she was hoping for on a Friday night or receiving too few trips can easily switch between offering trips on Uber or Lyft. For instance, third-party apps make this process seamless for drivers, allowing them to automatically switch between Lyft and Uber to optimize profits.¹⁴¹ The TLC data, articles, and surveys show that drivers do in fact

¹³⁸ “Prime” or “Surge” pricing refers to increased fares that Lyft and Uber implement during periods of peak demand. For example, the platforms may double the price of trips during peak hours in order to incentivize drivers to supply trips on the platform. “Prime Time only adds a percentage to the ride subtotal, which is calculated before the Service Fee, taxes and airport fees, or other additional amounts. For Shared rides, Prime Time is calculated based on the first passenger that a driver accepts in a chain” (“Prime Time for drivers,” *Lyft Help*, available at <https://help.lyft.com/hc/en-us/articles/115012926467-Prime-Time-for-drivers>). “In these cases of very high demand, fares may increase to help ensure those who need a ride can get one. This system is called surge pricing, and it lets us continue to be a reliable choice. [...] For example, you might see surge at 1.8x or 2.5x. This is how much your base fare will be multiplied by” (“How surge pricing works,” *Uber*, available at <https://www.uber.com/drive/partner-app/how-surge-works/>).

¹³⁹ “4 Apps that Compare Rideshare (Uber, Lyft, Juno, etc.) Prices and Wait Times,” *HelloTech: The Plug* (September 10, 2018), <https://www.hellotech.com/blog/4-apps-that-compare-rideshare-uber-lyft-juno-etc-prices-and-wait-times/>.

¹⁴⁰ Madrigal, Alexis C., “Will Uber and Lyft Become Different Things?,” *The Atlantic*, June 7, 2018 (“Yet over the last six years, as the two ride-hailing companies have been in direct competition around the nation, Uber and Lyft have essentially served as exact substitutes”).

¹⁴¹ A recent article describes one such app, Mystro: “Mystro aggregates jobs from Uber, Lyft, and (as of December) Postmates, and presents them to drivers on one screen; it also lets its 40,000 users set filters to

multi-home actively and commonly.¹⁴² Parrott and Reich themselves say that 45 percent of drivers multi-home and that multi-homing is increasing.¹⁴³ Survey evidence also suggests that multi-homing is high. For instance, The Rideshare Guy found in a 2018 poll of over a thousand drivers that nearly 80 percent are signed up for more than one platform (including Uber, Lyft, Postmates, and others).¹⁴⁴ Further, 20 percent of drivers split their driving hours evenly between Lyft and Uber, meaning that a larger share relies to a lesser extent on a single platform.¹⁴⁵

109. Common multi-homing suggests that there is already pressure on ridesharing platforms such as Lyft and Uber to engage in competition for drivers, leading to competitive pressure on the commission rate.¹⁴⁶ Indeed, if Lyft charged substantially higher commissions than Uber, it would be very easy for a driver to switch to Uber. Uber has faced competition in New York City from multiple rideshare services such as Lyft, Juno, Via, and Gett.¹⁴⁷ For example, when Uber lowered fares in New York, Gett responded by undercutting Uber's commissions by at least 10 percent in a bid to attract drivers to their platform with the offer of higher fares.¹⁴⁸

automatically accept or reject trips based on distance, surge pricing, passenger ratings, and more. As of a month ago, Mystro lets drivers do all that without taking their hands off the wheel." See, Katz, "This App Lets Drivers Juggle Competing Uber and Lyft Rides," *WIRED*, February 15, 2018.

¹⁴² See, e.g., Madrigal, "Will Uber and Lyft Become Different Things?," *The Atlantic*, June 7, 2018. ("Drivers seem to find them interchangeable, too, often suctioning two phones to their windshields—one for Uber, one for Lyft"); Parrott and Reich Report, Exhibit 19.

¹⁴³ Parrott and Reich Report, footnote 17 and p. 42 ("In October 2017, 55 percent of app drivers worked on only one platform"; "Importantly, an increasing proportion of drivers work with more than one app company").

¹⁴⁴ "2018 Uber and Lyft Survey Results," *The Rideshare Guy*, available at <https://therideshareguy.com/2018-uber-and-lyft-driver-survey-results-the-rideshare-guy/>.

¹⁴⁵ "2018 Uber and Lyft Survey Results," *The Rideshare Guy*, <https://therideshareguy.com/2018-uber-and-lyft-driver-survey-results-the-rideshare-guy/>.

¹⁴⁶ Rochet, Jean-Charles and Jean Tirole, "Platform Competition in Two-Sided Markets," *Journal of the European Economic Association*, Vol. 1, No. 4 (2003), p. 993 ("For example, when Visa reduces the (transaction-proportional) charge paid by the merchants, merchants become more tempted to turn down the more costly Amex card as long as a large fraction of Amex customers also owns a Visa card. More generally, multihoming on one side intensifies price competition on the other side as platforms use low prices in an attempt to "steer" end users on the latter side toward an exclusive relationship.").

¹⁴⁷ Hawkins, Andrew J., "Juno wants to woo Uber drivers with a more ethical ride-sharing app," *The Verge*, March 29, 2016 ("But the app I used wasn't Uber, nor was it Lyft, Gett, Via, Flywheel, Arro, Way2Ride, Curb, or any of the other dozens of ride-hail apps currently on the market.").

¹⁴⁸ Ziegler, Chris, "Gett is undercutting Uber's commissions in New York to entice unhappy drivers," *The Verge*, May 12, 2016.

110. The Parrott and Reich Report appears to contradict itself as to the extent to which it believes drivers multi-home and as to the consequences of such multi-homing. On the one hand, it cites data that drivers do multi-home extensively, explaining that “[t]his feature works against the likelihood that any one company will become a natural monopoly” and that “Lyft [and others] compete directly with Uber.”¹⁴⁹ However, when trying to portray the competitive landscape of the ridesharing industry, it ignores the implied competitive pressure that multi-homing introduces, namely that there is downward pressure on commission rates that ridesharing platforms can charge to drivers.¹⁵⁰ Consistent with the existence of such downward pressure, Parrott and Reich report that Uber reduced its commission rate from 25 in “its early days” to about 20 percent.¹⁵¹

ii. The Report is Mistaken in its Claim That Commissions are High and Therefore Incorrectly Claims Commissions Can Be Reduced

111. One of the central assumptions of Parrott and Reich’s calculation is that ridesharing platforms will lower their average commission rates by more than half. In the three scenarios deemed “plausible,” Parrott and Reich assume that the average commission rate will drop to 5.6 percent, 8.3 percent, and 10.1 percent, respectively, from a current level of 16.6 percent.¹⁵² After taking into account credit card fees that ridesharing platforms also need to pay, around 3 percent,¹⁵³ the assumed average commission rates net of credit card fees would be 2.6, 5.3, or 7.1 percent. This amounts to roughly a 50 percent to 80 percent decrease in net commissions.
112. Parrott and Reich’s assumption that such decreases in commission rates are possible, let alone “plausible,” lacks any basis in economics. Parrott and Reich claim that “even an 8.3 percent commission is well above the rate that would prevail under conditions of more effective competition in the industry.”¹⁵⁴ Parrott and Reich provide no explanation as to what “more

¹⁴⁹ Parrott and Reich Report, footnote 17 and p. 42.

¹⁵⁰ Ziegler, “Gett is undercutting Uber’s commissions in New York to entice unhappy drivers,” *The Verge*, May 12, 2016. See also, Katz, Miranda, “There’s Only One Way to Compete With Uber,” *WIRED*, September 2, 2016.

¹⁵¹ Parrott and Reich Report, pp. 43–44.

¹⁵² Exhibit 5 of this report shows how this assumption follows directly from Parrott and Reich’s assumptions regarding the average increase in driver pay, the average fare increase, and the price elasticity of demand.

¹⁵³ Lyft’s share of credit card transaction fees is roughly 3–4% based on data from Wojciechowska, Iza, “The cost of splitting the bill,” *Fin*, April 20, 2016.

¹⁵⁴ Parrott and Reich Report, p. 58.

effective competition” would be, or why they ignore the economic factors that push towards intense competition such as multi-homing. Parrott and Reich’s assumption that ridesharing platforms would voluntarily choose to slash their commission rates in response to the TLC’s minimum payment requirement is unsupported and illogical for several reasons.

a. No evidence that commissions are high

113. To support the idea that ridesharing platforms’ commission rates are high and that there is room to lower commissions, Parrott and Reich claim that “[w]hile oligopolies [sic] compete with each other, they retain considerable market power. This power is most evident in their high price mark-ups over costs (Hall 2018).”¹⁵⁵
114. First, Parrott and Reich appear to suggest that oligopolists must have market power, though the paper they cite does not find evidence that sectors with the largest firms have higher price/marginal cost markups.¹⁵⁶ Some recent economic research also suggests that industries experiencing faster technical change have seen increased concentration, suggesting that technological dynamism, rather than anticompetitive forces, is an important driver of the increase in concentration.¹⁵⁷
115. However, Parrott and Reich have not performed any analysis to show that this is the case for Uber, Lyft, or any other ridesharing platform. Parrott and Reich do not analyze ridesharing platforms’ costs in arriving at their conclusion that they have “high price mark-ups over costs.” Instead, they report that “we conservatively estimate that these operating costs for Uber’s New York City business add up to roughly \$50 million per year.”¹⁵⁸ They do not provide details on how they estimated this number.

¹⁵⁵ Parrott and Reich Report, p. 43.

¹⁵⁶ Hall, Robert E., “New Evidence on the Markup of Prices Over Marginal Costs and the Role of Mega-Firms in the U.S. Economy,” (National Bureau of Economic Research; 2018), p. 3.

¹⁵⁷ Autor, David et al., “The Fall of the Labor Share and the Rise of Superstar Firms,” (National Bureau of Economic Research; 2017), p. 25.

¹⁵⁸ Parrott and Reich Report, p. 45.

b. Inappropriate cross-industry comparisons

116. Parrott and Reich’s comparisons to commission rates in other industries do not provide an apples-to-apples comparison. Parrott and Reich compare the average ridesharing platforms’ commission rate with those of certain other platforms, claiming without support that “the app industry falls somewhere between e-commerce retailers and credit card companies.”¹⁵⁹ Such a broad cross-industry comparison is unsupported economically, without first conducting an inquiry into the competitive conditions, nature and size of typical purchases, and firms’ cost structures in these industries.
117. Credit card payment networks are not an appropriate comparison to the ridesharing industry. As part of the pay transaction, ridesharing platforms also use credit cards and have to pay processing fees to credit card companies. Therefore, commission rates from ridesharing platforms will be higher than those charged by credit card companies to account for the additional transaction costs associated with credit card fees. Credit card fees could cost an upward of 3.8 percent for Uber and 4.0 percent for Lyft as a share of an average ride.¹⁶⁰ In addition, debit cards are charged at a “flat processing fee of up to \$0.21 per transaction” or around 1.7 percent of an average Lyft ride.¹⁶¹
118. Moreover, the commission rates of ridesharing platforms in New York City, on average 16.6 percent, do not appear to be higher than other digital platforms. **Exhibit 8** provides a comparison of commission rates among digital platforms. Platforms that charge commission rates similar to ridesharing platforms include large, established companies like Amazon and smaller startups like DoorDash. These companies also make money on other fees. For example, Amazon charges per item fees as referral fees in addition to percentage commissions.

¹⁵⁹ Parrott and Reich Report, p. 44.

¹⁶⁰ According to SherpaShare data, an average Uber and Lyft trip costs \$13.36 and \$12.53, respectively, and credit card fees could cost upwards of \$0.50. See Wojciechowska, “The cost of splitting the bill,” *Fin*, April 20, 2016.

¹⁶¹ Wojciechowska, “The cost of splitting the bill,” *Fin*, April 20, 2016.

Exhibit 8
Comparison of Commissions¹⁶²

Company	Year	Commission	Description
Amazon	2019	6–15%	Depending on the item category, individual sellers are charged between 6 percent and 15 percent on the final amount charged. Also, depending on their classification as an independent or professional seller, they are charged a per-item listing fee or a flat monthly subscription fee, respectively.
eBay	2019	2–12%	Depending on the item category and seller rating, eBay charges fees ranging from 2% to 12%. Sellers are also charged an “insertion fee” to list items on the platform.
DoorDash	2018	20%	“DoorDash makes money through a commission fee to restaurants of around 20%, as well as delivery and service fees.”
Groupon	2019	15%	“Regarding fees, the only standard fee that gets charged is a 15% default referral fee (commission), based on (list price + shipping).”
GrubHub	2018	15–30%	“Non-sponsored listing: For a 15 percent commission rate (again, this is in my area of New York City; check your local rates) your restaurant will be posted on Grubhub [...] Sponsored listing: For a commission rate of 20 percent or higher, your restaurant will be posted on Grubhub and it will be prioritized [...] it is not uncommon for restaurants in densely populated areas to spend 30 percent or more for better spots on the page”
Postmates	2015	20%	“[...]average delivery payout is \$7–\$8 and there is a 20% commission (the customer pays a 9% service fee directly to PM) paid to Postmates, similar to Uber and Lyft. Delivery payouts range from \$5–\$18 (after commission) and are determined solely by distance from pick-up to drop-off.”
Shutterstock	2019	70–80%	“Enhanced license On Demand downloads will generate earnings of 20–30% from the purchase price, depending on your Lifetime Earnings tier. [...] All footage clip downloads will earn you 30% of the purchase price paid by the customer.”
StubHub	2015	15–17%	“On Tuesday, however, StubHub announced that it will shift back to the previous model of listing lower prices and adding 15% to 17% in fees right before checkout”

Note: Commissions can vary from the stated values depending on specific circumstances. For example, the eBay commission may be higher if the seller’s rating is not satisfactory.

c. Variation in fares is not evidence of market power

119. Parrott and Reich argue that “[t]he companies’ price-setting power is also evident in how they vary their prices by neighborhoods and routes.”¹⁶³ Their argument appears to confuse the ability to set rider fares, with the ability to set commission rates, which is the relevant price for assessing market power.
120. Parrott and Reich cite a *Bloomberg.com* article which describes Uber’s practice of charging different prices for different routes and neighborhoods, even at the same time of day within the same city.¹⁶⁴ However, they ignore the platform economics literature which suggests that such forms of demand-based pricing may not reflect a lack of competitive pressure. Instead, the literature suggests that price-discrimination may reflect either a great deal of competitive pressure or little competitive pressure.¹⁶⁵ Indeed, one paper highlights that the complexity of price schedules may reflect more competitive pressure.¹⁶⁶

¹⁶² “Selling on Amazon Fee Schedule,” *Amazon Seller Central*, available at https://sellercentral.amazon.com/gp/help/external/200336920/ref=asus_soa_p_fees?ld=NSGoogle; “Selling Fees,” *eBay Customer Service*, available at <https://www.ebay.com/help/selling/fees-credits-invoices/selling-fees?id=4364>; Bensinger, Greg, “DoorDash More Than Doubles Valuation to \$4 Billion,” *Wall Street Journal*, August 16, 2018; “Getting Started: New Merchant,” *Groupon Goods Marketplace*, available at <https://marketplace.groupon.com/support/solutions/articles/5000726074-getting-started-new-merchant>; Bushnell, Mona, “Should Your Restaurant be on GrubHub?,” *Business.com*, January 8, 2018; Campbell, Harry, “10 Things I Learned At My Postmates Orientation,” *The Rideshare Guy* (April 13, 2015), <https://therideshareguy.com/10-things-i-learned-at-my-postmates-orientation/>; “How much will I be paid as a contributor to Shutterstock?,” *Shutterstock*, available at https://www.shutterstock.com/contributorsupport/articles/en_US/kbat02/000006640?l=en_US; Osborn, Katy, “Why StubHub is Tacking on Ticket Fees Again,” *Money*, September 1, 2015.

¹⁶³ Parrott and Reich Report, p. 44.

¹⁶⁴ Newcomer, Eric, “Uber Starts Charging What It Thinks You’re Willing to Pay,” *Bloomberg*, May 19, 2017.

¹⁶⁵ Gil, Ricard and Daniel Riera-Crichton, “Price Discrimination and Competition in Two-Sided Markets: Evidence from the Spanish Local TV Industry,” (IESE Research Papers; February 2012, 2012).

¹⁶⁶ Busse, Meghan and Marc Rysman, “Competition and Price Discrimination in Yellow Pages Advertising,” *RAND Journal of Economics*, Vol. 36, No. 2.

V. THE PER TRIP CALCULATION REQUIREMENT OF THE MINIMUM PAYMENT RULE HAS NO ECONOMIC BASIS

A. There Is No Economic Foundation for the Per Trip Calculation Requirement of the Minimum Payment Rule

121. The TLC’s proposed Minimum Payment Rule would establish a payment floor based on the length and duration of trips provided by drivers. The Minimum Payment Rule requires that the minimum amounts be paid “for each trip dispatched by the Base.” In their Report, Parrott and Reich provide no justification as to why the Minimum Payment Rule should be calculated at the per-trip level (the Per Trip Calculation Requirement). Further, the Report even explains that the Minimum Payment rule could be applied for a given time period, such as a week or a month:

TLC regulations will specify the precise means by which the pay standard will be implemented. Generally, for a set time period (such as a week or a month), companies will evaluate each driver’s earnings using the total trip mileage and trip minutes for that company. If the compensation provided to a driver falls below the minimum pay standard, the companies will be required to make up the difference.¹⁶⁷

122. Moreover, Parrott and Reich fail to evaluate the Per Trip Calculation Requirement of the Minimum Payment Rule, and they do not analyze how drivers’ earnings, either per trip or overall, would be affected by the Per Trip Calculation Requirement. For instance, in the Supplementary Report, when they “summarize the key results from the driver-level earnings analysis,” they only provide hourly and weekly estimates.¹⁶⁸
123. In addition, the “simulation” of the alleged effect of the Minimum Payment Rule is not based on the Per Trip Calculation Requirement. Rather, in the Report, Parrott and Reich use an assumed increase in average hourly earnings, and in the Supplementary Report, they use an assumed increase in weekly aggregate gross pay.¹⁶⁹ As such, none of the simulations in either report incorporates the Per Trip Calculation Requirement of the Minimum Payment Rule they purport to analyze.

¹⁶⁷ Parrott and Reich Report, pp. 35–36.

¹⁶⁸ Parrott and Reich Supplementary Report, Exhibit 7.

¹⁶⁹ I note that while Parrott and Reich evaluate the effects of an average increase in aggregate weekly pay, the likely effects of an average increase would differ from the effects of a per-week formulation of the Minimum Payment Rule, which I discuss in V.B.iv.

124. As I explain in the remainder of this section, a Per Trip Calculation Requirement, because it does not affect driver’s pay for each trip uniformly, does not have the same effect as changing the average hourly earnings. Parrott and Reich’s “simulation” cannot form the economic basis for the Per Trip Calculation Requirement of the Minimum Payment Rule when their approach is premised instead on changes in average hourly pay on a weekly basis or aggregate weekly pay.

i. Key Earnings Analyses in the Parrott and Reich Report Focus on Longer Time Periods

125. When evaluating driver earnings in the FHV market, the Report never considers per trip earnings. Instead, Parrott and Reich present several summary tables on driver earnings, and in every table they evaluate average hourly driver earnings on a per week basis. In Exhibit 6, Exhibit 9, Exhibit 11, Exhibit 12, and again in their “simulation,” Parrott and Reich estimate “hourly earnings for each study week.”¹⁷⁰ Their headline finding from the review of driver earnings is that “to bring the average worker below the standard up to the \$17.22 floor, gross hourly earnings would need to rise by 14 percent.”¹⁷¹ Notably, they calculate hourly earnings as the average hourly earnings during the course of a week, instead of a per trip basis.
126. In the Supplementary Report, “the key results from the driver-level earnings analysis” are summarized in Exhibit 7, in which Parrott, Reich, Rochford, and Yang only provide hourly and weekly estimates.¹⁷² As in the Report, they mention that “[t]o raise all below-minimum trips up to the minimum standard level would entail a 20.7 percent increase in weekly aggregate gross pay.”¹⁷³

ii. The Effect of the Per Trip Calculation Requirement Has Not Been Evaluated by the Reports

127. Rather than analyze how trips will be affected by the Per Trip Calculation Requirement of the Minimum Payment Rule, both reports instead evaluate a uniform “average increase in driver

¹⁷⁰ Parrott and Reich Report, pp. 20, 24, 29–30 and 59–60. For Exhibits 11 and 12, Parrott and Reich limit their analysis of hourly earnings to the week of October 15, 2017.

¹⁷¹ Parrott and Reich Report, p. 32.

¹⁷² Parrott and Reich Supplementary Report, Exhibit 7.

¹⁷³ Parrott and Reich Supplementary Report, p. 5.

pay.”¹⁷⁴ Parrott and Reich’s shortcut of assuming a uniform increase does not consider whether a trip will in fact be affected by the Per Trip Calculation Requirement of the Minimum Payment Rule nor does it provide any insight as to how a change in driver cost for specific trips would affect rider and driver behavior. As such, their “simulation” is disconnected from the relevant policy question and incapable of providing meaningful predictions of the effects of the Minimum Payment Rule and the Per Trip Calculation Requirement. A consequence of this shortcut approach is that neither report evaluates the effects of the Minimum Payment Rule and the Per Trip Calculation Requirement directly.

128. In addition, in the Report, the 13.2 percent increase in drivers’ gross hourly pay that Parrott and Reich calculate and use as starting point for their analysis is not related to the specific Minimum Payment Rule and the Per Trip Calculation Requirement that they claim to evaluate. Rather than calculating what driver earnings would have been under the proposed Minimum Payment Rule and the Per Trip Calculation Requirement, they calculate the difference between \$17.22 and average hourly pay for all the drivers in their sample for the week of October 15, 2017.¹⁷⁵ Such a calculation is incorrect because, as I explain below in Section V.B, the effect of a uniform change in driver pay is not the same as the effect of heterogeneous changes across trips.
129. The Supplementary Report fails to address this issue. Rather, Parrott and Reich continue to rely on their shortcut approach of analyzing the effect of a 20.7 percent uniform increase in “weekly aggregate gross pay” rather than a per trip simulation of how the Per Trip Calculation Requirement would affect the market.

iii. The Per Trip Calculation Requirement Necessarily Overshoots the Minimum Payment Objective Compared to a Per Week Calculation Requirement

130. A Per Week Calculation of the Minimum Payment Rule would still ensure that the Minimum Payment Requirement’s objective is achieved, but it would do so for the average trip, not for each

¹⁷⁴ Parrott and Reich Report, p. 58 and Parrott and Reich Supplementary Report, p. 7 (“Implications of the 20.7 percent aggregate pay increase for passenger fares and commission rates”). An aggregate pay increase is no different from a uniform average increase.

¹⁷⁵ Parrott and Reich Report, Exhibit 12.

trip individually. In contrast, the Per Trip Calculation Requirement of the Minimum Payment Rule will likely lead to changes in earnings greater than the objective.

131. To apply the Minimum Payment Rule on a weekly basis, a ridesharing platform would simply calculate each driver's total miles driven and total trip minutes for the week and then apply the formula to those totals. This is straightforward because the TLC's proposed formula is simply the sum of a mileage component (to cover the driver's expenses) and a time factor (to cover the driver's time). For example, applying the formula at the weekly level, a driver who spends 30 hours transporting riders and covers 240 trip miles during the span of a week would earn at least \$1,151.79 for the week, where \$261.10 covers the driver's total expenses for the week and \$890.69 covers the driver's total driving time for the week.¹⁷⁶ Suppose the driver was active for a total of 51.72 hours that week, meaning her utilization was 58 percent.¹⁷⁷ Then the driver's total weekly pay corresponds to an effective Minimum Payment Requirement (net of expenses) of \$17.22 per hour.¹⁷⁸ In other words, under Lyft's current compensation structure, each individual trip taken by the driver may currently be above or below the Minimum Payment Requirement, but the Per Week Calculation of the Minimum Payment Rule works to ensure the Minimum Payment Requirement on average — at average utilization and expenses, a driver will earn the Minimum Payment Requirement.
132. Now consider what the driver's total weekly earnings would be under the Per Trip Calculation Requirement. The calculation is now more complicated, because for the Per Trip Calculation Requirement the types of trips the driver received during the span of the week matters, even if the total hours and miles driven remain unchanged. To the extent that Lyft's current compensation for any one trip is below that of the Minimum Payment Requirement, the Per Trip Calculation Requirement will enforce a payment increase for each such trip. The Per Trip Calculation Requirement precludes trips taken during the course of the week to even out trip-level fluctuations in earnings by forcing each trip that is currently below the Minimum Payment Requirement to be

¹⁷⁶ $\frac{\$0.631}{0.58} \times 240 + \frac{\$0.287}{0.58} \times 30 \times 60 = \$261.10 + \$890.69 = \$1,151.79$

¹⁷⁷ $\frac{30}{0.58} = 51.72$

¹⁷⁸ $\frac{\$890.69}{51.72} = \17.22

at the Minimum Payment Requirement. Therefore, on average, the driver will necessarily be above the Minimum Payment Requirement.¹⁷⁹

B. The Per Trip Calculation Requirement of the Minimum Payment Rule Creates Distortions

i. The Per Trip Calculation Requirement Affects Drivers' Payments on Some Trips More than Others, Distorting Drivers' Incentives

133. The Per Trip Calculation Requirement of the Minimum Payment Rule will disproportionately affect driver payments for certain types of trips, thereby distorting drivers' incentives and creating negative downstream effects, such as increased congestion and longer rider wait times.
134. In particular, the Per Trip Calculation Requirement of the Minimum Payment Rule affects driver incentives and alters their behavior. Riders' need for ridesharing transportation (demand) and app-drivers' availability (supply) varies both geographically and over time, and ridesharing platforms have developed complicated algorithms to ensure that demand and supply for trips are matched at all times. One of the most important mechanisms that ridesharing platforms use to accomplish this balance is through changes in price and drivers' payments through peak pricing. As I explained in Section 23, drivers are paid more during peak pricing periods, and fares are also increased. Because the Per Trip Calculation Requirement of the Minimum Payment Rule will raise driver payments and rider prices for some trips more than others, also leaving some trips unaffected, the relative difference in the price increase induced by the Per Trip Calculation Requirement will change drivers' incentives and create distortions.
135. Specifically, the Per Trip Calculation Requirement will likely: (1) create geographic locations and time periods with significantly more supply than demand, and increase congestion; and (2) create geographic locations and time periods with significantly lower supply than demand. In addition, the Per Trip Calculation Requirement reduces the incentives for drivers to drive during peak times.

¹⁷⁹ To the extent that at least one of the driver's trips during the week is above the objective implies that, for any longer time period, such as a week, the driver will necessarily be above the objective on average. Parrott, Reich, Rochford, and Yang claim that over 27 percent of the trips are above the target (Supplementary Report, Exhibit 6), which means it is likely that a driver will have at least one trip above the target. Assuming the likelihood of getting a trip above the target is the same for all drivers and each trip is independent, the likelihood of getting all trips at the target is under 1 percent for a driver who drives 15 trips ($0.73^{15} = 0.9$ percent).

As a result, the algorithm developed by ridesharing platforms designed to achieve the aims of Equilibrium, Enticement, and Evolution described in Section III.A will not be able to achieve them as easily. These distortions will hurt riders and drivers.

136. **Exhibit 9** illustrates the percentage increase in driver pay after the imposition of the Minimum Payment Rule compared to Lyft's current payment structure, for non-peak times. The Minimum Payment Rule is binding on nearly all trips, except for very short-duration trips. However, the increase in driver pay varies substantially across different types of trips. For example, a driver who drives for 45 minutes and covers five miles (conditions that can occur during periods of high congestion) would experience an increase in payment of approximately 50%, while another driver who drives for 15 minutes and covers 10 miles (conditions more common during periods of low congestion) would only experience a 7% increase in payment.

Exhibit 9
Percent Increase in Per Trip Driver Pay Due to the
Per Trip Calculation Requirement of the Minimum Payment Rule

		Trip Minutes											
		5	10	15	20	25	30	35	40	45	50	55	60
Trip Miles	5		3%	14%	23%	31%	37%	42%	46%	50%	54%	57%	59%
	10			7%	13%	19%	24%	28%	32%	36%	39%	42%	45%
	15				8%	13%	17%	21%	24%	27%	30%	33%	36%
	20					9%	12%	16%	19%	22%	24%	27%	29%
	25						9%	12%	15%	17%	20%	22%	24%
	30								12%	14%	16%	19%	21%
	35									12%	14%	16%	18%
	40										12%	14%	15%
	45											12%	13%
	50												12%

Notes:

- [1] The percent increase in driver pay for a trip is calculated by taking the maximum of Lyft's driver payment rate and the Minimum Payment Rule and dividing by Lyft's driver payment rate.
- [2] Lyft's driver payment rate is $\$1.7175 + \$1.185 \times \text{miles} + \$0.24 \times \text{minutes}$, or Lyft's minimum trip payment, whichever is higher. Lyft's minimum trip payment to a driver is \$5.3925 or \$5.752, depending on when the driver signed up for the app. For the purposes of this report, I assume the minimum is \$5.752.
- [3] Combinations of miles and minutes that imply an average speed greater than 50 miles per hour are omitted.

137. As drivers have the flexibility to choose where and when to drive, they have the latitude to behave strategically to try to maximize their earnings, for instance by choosing the times or the locations

that will get them the highest pay.¹⁸⁰ The relative difference in price increases imposed by the Per Trip Calculation Requirement of the Minimum Payment Rule makes some trips more attractive than others, and will likely incentivize drivers to shift to geographic locations and time periods that are relatively more profitable to them. Drivers may therefore change when they drive, where they drive (to the extent that location may determine time/distance ratios and/or peak pricing), and the types of trips they choose to accept.¹⁸¹

138. The Per Trip Calculation Requirement of the Minimum Payment Rule will likely further exacerbate congestion in areas that are already congested, all else equal. **Exhibit 10** illustrates the percent increase in driver pay relative to Lyft’s current payment structure for low and high congestion locations and time periods and for three types of drivers with (1) low, (2) average, and (3) high utilization. The Per Trip Calculation Requirement of the Minimum Payment Rule disproportionately increases driver pay for high congestion locations and time periods (for example, at a rate of 63 percent for high congestion and high utilization periods), while affecting low congestion locations and time periods much less (for example, at a rate of 16 percent for low congestion and low utilization periods).
139. The Per Trip Calculation Requirement of the Minimum Payment Rule incentivizes drivers to switch from driving in low utilization/low congestion settings to driving in high congestion/high utilization settings. Under Lyft’s current payment rates, low utilization/low congestion settings yield higher average hourly pay (\$20.42 per hour) than high utilization/high congestion settings (\$16.55 per hour), incentivizing drivers to drive more in low utilization/low congestion settings.¹⁸²

¹⁸⁰ Campbell, *The Rideshare Guide* (2018), Chapter 5; Flanagan, Jack, “How much do Uber drivers really make?,” *The Daily Dot*, June 20, 2014 (“Smart” drivers will “pack in the hours during the most lucrative times. A ‘smart’ driver only works during the best hours (mornings and late evenings). He tries to get in all the airport runs he can (because airport fares are better than average hauls, and usually come in twos: one there, another back). And he works ‘surge hours’—the times when Uber multiplies pricing during high demand”).

¹⁸¹ Drivers have about ten seconds to accept a new trip when it is assigned to them; by doing nothing, the driver effectively declines the trip. Ridesharing platforms impose some restrictions on drivers’ to ensure high acceptance rates — for example, locking a driver out of the app after declining to accept multiple trips in a row. However, drivers may still choose to behave strategically when accepting trips (“The best advice I can give you when it comes to being a more cutthroat rideshare driver is that you don’t have to take every ride” Campbell, *The Rideshare Guide* (2018), pp. 40, 74–77).

¹⁸² Average hourly driver pay is calculated by assuming that a driver drives one trip per hour. These results can also approximate average hourly pay for drivers with multiple trips within an hour. For drivers with multiple

Exhibit 10
Percent Increase in Driver Pay

Congestion	Low	Average	High
High	47%	56%	63%
Low	16%	19%	21%

Notes:

[1] High congestion is defined as average trip speed less than 6 miles per hour.¹⁸³

[2] Utilization is calculated assuming one trip per hour, but these results can also approximate percent increases in driver pay for drivers with multiple trips per hour (see footnote 182). Average utilization is assumed to be 0.58.

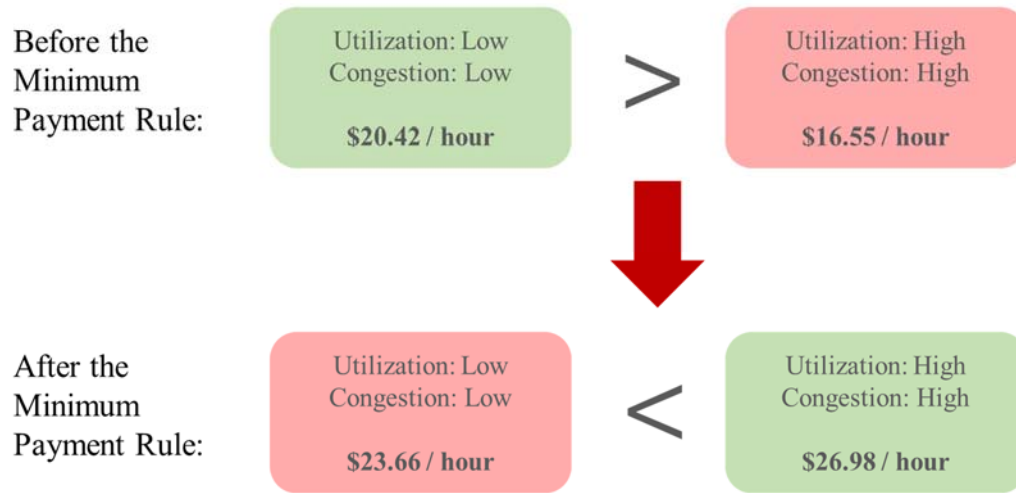
[3] Percent increases are calculated as the overall percent increase for all trips in the corresponding category. Trips are defined in increments of 0.1 miles and 0.1 minutes, with lower bounds of 0.5 miles and 5 minutes, and excluding trips with implied average speed greater than 50 mph.

140. As shown in **Exhibit 11**, this relationship switches after the Minimum Payment Rule is implemented: high utilization/high congestion settings yield higher average hourly pay (\$26.98 per hour) than low utilization/low congestion settings (\$23.66 per hour), making high utilization/high congestion settings more attractive. This will cause some drivers who drove in low utilization/low congestion settings to switch to high utilization/high congestion settings, but the reverse is not true. A driver who previously drove in a high utilization/high congestion area will not want to switch to a low utilization/low congestion area. Such a driver already preferred high utilization/high congestion settings even when she was paid less than she could have been paid elsewhere. The driver will experience a large pay increase from \$16.55 per hour to \$26.98 per hour, and she will have no reason to switch to a low utilization/low congestion setting and earn \$23.66 per hour. This discussion highlights the extent to which any analysis of a new proposed payment structure has to encompass questions of “Evolution” as discussed in Section III.A — the current proposed Per Trip Calculation Requirement of the Minimum Payment Rule will lead to dynamics whereby congestion will increase in non-peak times.

trips per hour, the percent increase in pay will be lower than what is reported in Exhibit 10 due to Lyft’s base payment for each trip. To the extent that some of a driver’s trips hit the payment floor imposed by the Minimum Payment Rule and others do not, the average hourly pay may vary from what is reported in Exhibit 10 and Exhibit 11.

¹⁸³ Bliss, Laura, “How to Fix New York City’s ‘Unsustainable’ Traffic Woes,” *CityLab*, December 21, 2017.

Exhibit 11
The Per Trip Calculation Requirement of the Minimum Payment Rule
Increases Congestion



Notes:

[1] Green boxes indicate settings with higher hourly pay for the corresponding payment policy.

[2] Hourly payment rates are based on averages for the given utilization-congestion combination.

[3] High utilization is defined as utilization greater than 0.58, and high congestion is defined as an average trip speed of less than 6 miles per hour.

141. In addition to creating congestion during non-peak times, the Per Trip Calculation Requirement of the Minimum Payment Rule will also reduce ridesharing platforms’ ability to incentivize drivers during peak times. Indeed, during peak times — that is, times of especially high demand — platforms such as Lyft and Uber pay their drivers more to induce them to provide more trips in locations where demand is high or at times when demand is high. Because the Per Trip Calculation Requirement of the Minimum Payment Rule is likely to have a disproportionately larger effect on non-peak pricing than on peak pricing, it will reduce drivers’ incentives to drive during peak times. This will result in a shortage of drivers during periods where riders have high demand, resulting in higher rider prices and longer wait times. As such, this distorts the ability of the platform to achieve “Equilibrium,” as discussed in Section III.A — to the detriment of the platforms’ users.

ii. The Per Trip Calculation Requirement Affects Fares on Some Trips More than Others, Likely Decreasing the Number of Trips

142. By disproportionately affecting driver payments on certain types of trips, the Per Trip Calculation Requirement of the Minimum Payment Rule is also likely to disproportionately affect rider fares.

As a result, the total number of trips is likely to decrease, which ultimately harms drivers and may reduce the overall efficiency of the platform.

143. Because the relative changes in driver pay resulting from the Per Trip Calculation Requirement of the Minimum Payment Rule vary across trips, the fares for some trips may increase a lot more than others. In general, higher prices will likely be necessary to cover the cost of implementing the Minimum Payment Requirement. Given that the percentage increase in earnings due to the Per Trip Calculation Requirement for a significant share of mile and minute combinations is higher than Lyft's current effective commission rate of 25 percent (as shown in **Exhibit 9**), the price of such trips will necessarily have to increase in order for Lyft to at least break even on such rides.¹⁸⁴
144. From a policy perspective, increasing the prices of trips that have the least elastic demand is better for drivers because this will lead the smallest reduction in quantities. This is a principle of optimal taxation. If quantity is reduced, it becomes more difficult for drivers to earn the minimum hourly pay even if they earn higher pay per trip, because utilization will tend to decrease. However, Parrott and Reich did not account for this in designing the Minimum Payment Rule and they present no evidence to suggest that the trips for which the price is likely to increase the most are the trips for which demand would be least affected by a price change.
145. In fact, common sense suggests the opposite. All else equal, riders needing to travel shorter distances are more likely to consider alternative means of transportation, such as walking or riding a bicycle. In addition, the heavier the traffic, the more likely it is that riders would consider other means of public transport, such as taking the subway. These considerations imply that, all else equal, riders' price elasticity of demand is higher for shorter distances than longer distances, as well as during periods of high congestion compared to periods of low congestion. Therefore, the Per Trip Calculation Requirement of the Minimum Payment Rule, which induces drivers to shift their supply toward shorter trips during periods of high congestion, imposes the highest relative

¹⁸⁴ If a platform takes a 20 percent commission rate off the rider fare, then the rider fare is 25 percent higher than the driver pay (driver pay = $0.8 \times$ rider fare, which implies rider fare = $1.25 \times$ driver pay). Therefore, the relevant threshold for comparing percent increases in driver pay to the platform's commission rate is 25 percent.

price increases on trips and riders with higher price elasticity of demand, contrary to the theory of optimal taxation.¹⁸⁵

146. This is particularly salient for shared trips, as Parrott and Reich suggest imposing a \$1 per pick-up bonus to drivers for shared trips. This increase in the cost of shared trips may reduce demand for shared trips to the extent that the bonus increase is passed through to rider fares. It is likely that riders who opt for shared trips are the most price sensitive. For example, business riders would tend not to use shared trips, and they tend to be less price sensitive than the average rider. In contrast, students and low-income riders are more likely to use shared trips, and they are more price sensitive — a small increase in the price of an Uber or Lyft trip may induce such riders to take a bus, train, or walk. Therefore, increasing the fare of shared trips by \$1 is likely to lead to a much greater reduction in demand than increasing the fare for a trip taken for business by \$1.
147. All else equal, lower demand will hurt drivers; however, a more careful allocation of price increases across trips and riders could mitigate the reduction in demand. For example, suppose the least price sensitive trips' (such as those for business purposes) price elasticity of demand is 20 percent lower than that of the trips most affected by the Per Trip Calculation Requirement of the Minimum Payment Rule. Imposing the same price increase on this trip segment would yield a smaller reduction in demand (20 percent lower), which would likely be a more desirable outcome from a policy perspective. Ridesharing platforms are in a much better position to identify the least price sensitive trips and therefore could achieve the same Minimum Payment Requirement with likely lower reductions in demand than that caused by the arbitrary and distortionary price increase of the Minimum Payment Rule applied on a Per Trip basis.

¹⁸⁵ Whether the combination of drivers' shift to more congested areas and riders' reduced demand due to higher prices caused by the Per Trip Calculation Requirement would increase overall congestion or reduce it is an empirical question. The relatively greater increase in driver pay for short distance, high congestion trips will induce drivers to spend more hours driving in these high congestion areas — leading to more cars in already congested areas. However, riders' high elasticity of demand for these trips will lead to a reduction in trips demanded as fares increase. A more rigorous simulation would be required to determine the equilibrium outcome of the Per Trip Calculation Requirement on high congestion areas. Parrott and Reich did not conduct such an analysis.

iii. Ridesharing Platforms Already Employ Various Non-Distortionary Schemes to Ensure that They Compensate for Periods of Low Demand

148. In fact, ridesharing platforms have already devised various mechanisms that do not suffer from the distortionary shortcomings discussed in Section V.B, and which nevertheless still ensure that drivers earn certain minimum levels of compensation. These fall under the category of “Enticement” in platform pricing strategy — platforms need to ensure there is sufficient enticement to drivers and riders to enter and then continue to be part of the system.
149. Lyft offers various types of guaranteed compensation schemes that ensure that drivers “earn a guaranteed amount for completing a certain number of trips in a set amount of time.”¹⁸⁶ Lyft offers such guarantee promotions on a weekday, weekend, and weekly basis. For example, Lyft sometimes offers incentives such as a \$100 Earnings Guarantee for completing five trips on a Thursday. If a driver completes the required five trips but earns, say, only \$90, the driver receives a lump sum payment for the \$10 difference.¹⁸⁷ Uber sometimes offers guaranteed earnings promotions for new drivers that work in similar fashion. As described on its website, Uber in some scenarios offers compensation schemes that guarantee \$100 for completing 10 trips within 90 days, and if a new driver completes 10 trips in 90 days but only earns \$50, then Uber will pay the driver an additional \$50.¹⁸⁸ Uber also offers two types of weekly promotions for existing drivers: (1) Quest — which gives drivers a cash bonus for completing a certain number of trips within a certain time period such as a week or weekend, and (2) Boost — which guarantees higher earnings in certain featured locations during busy hours.¹⁸⁹
150. Such pricing schemes are designed to meet riders’ demand in geographic regions and time periods of low supply. If Lyft perceives that there are insufficient drivers on the road in a particular region

¹⁸⁶ “Earnings Guarantee Promotions,” *Lyft*, available at <https://help.lyft.com/hc/en-us/articles/115012927247-Earnings-Guarantee-promotions>.

¹⁸⁷ “Earnings Guarantee Promotions,” *Lyft*, <https://help.lyft.com/hc/en-us/articles/115012927247-Earnings-Guarantee-promotions>.

¹⁸⁸ “Guaranteed earnings offer for new drivers,” *Uber*, available at <https://www.uber.com/drive/partner-app/new-driver-guarantees/>.

¹⁸⁹ “Weekly Promotions: Your chance to earn more,” *Uber*, available at <https://www.uber.com/drive/resources/promotions/>. See also, Campbell, *The Rideshare Guide* (2018), pp. 66–70.

on a particular day, the platform might launch a promotion to incentivize drivers to drive more. Unlike the Per Trip Calculation Requirement of the Minimum Payment Rule, these pricing schemes are beneficial for both drivers and riders: drivers receive the additional compensation as a lump sum at the end of the day or week, and more drivers on the road implies less surge pricing reducing prices paid by riders. Importantly, such pricing schemes do not distort drivers' incentives associated with peak or surge pricing algorithms.

151. Moreover, the use of such guaranteed compensation schemes and other driver bonuses and incentives by Lyft and other ridesharing platforms is an indicator that they are competing for drivers. If Lyft and other ridesharing platforms had no trouble getting sufficient number of drivers to be active in each geographic region and time period, then there would be no need for these incentives — the ridesharing platform would be able to pay drivers lower rates while meeting demand. Contrary to Parrott and Reich's claims that ridesharing platforms retain considerable market power,¹⁹⁰ the fact that Lyft and other ridesharing platforms need to offer drivers incentives is evidence that ridesharing platforms do not have sufficient market power to unilaterally set driver pay, as drivers can switch from one platform to another. In platform pricing, when we see evidence of pricing structures focused on "Enticement" — as discussed in Section III.A — it is evidence that platforms are vigorously competing for platform users.
152. These compensation mechanisms are evidence that Lyft is already trying to optimize platform pricing. The effectiveness of the platform relies on matching supply and demand during varying conditions throughout the day, week, and time of year. If there are not enough drivers, then riders will experience longer wait times and become discouraged from using the app, and they will look for another platform or mode of transportation. Likewise, if demand is low and drivers spend too much time waiting for trips, then they will become discouraged with the platform and will look for another ridesharing platform or a different source of earnings. To ensure that drivers and riders can interact with the platform seamlessly, ridesharing platforms exert substantial effort to optimize platform pricing, including designing driver incentives and peak or surge pricing algorithms. The Per Trip Calculation Requirement of the Minimum Payment Rule is a blunt instrument that does not have any regard for the sophisticated pricing mechanisms that are required to make the

¹⁹⁰ Parrott and Reich Report, p. 43.

platform operate efficiently. The Per Trip Calculation Requirement will disrupt the platform's ability to ensure the platform is in Equilibrium, its ability to ensure sufficient Enticement to launch new initiatives and entice new users, and its ability to Evolve flexibly. In short, it will impede Lyft's ability to continue to deliver value to drivers and riders.

iv. A Per Week Calculation of the Minimum Payment Rule Would Result in Fewer Distortions

153. Compared to the Per Trip Calculation Requirement of the Minimum Payment Rule, a Per Week Calculation of the Minimum Payment Rule will cause fewer distortions. As discussed in Section V.B.i, the Per Trip Calculation Requirement makes certain trips more attractive than others to drivers, creating incentives for drivers to seek out those trips with the largest payment increases resulting from the Minimum Payment Rule. In contrast, a weekly rule does not cause any one trip to become significantly more attractive than another, because the rule aggregates across all trips that a driver makes. As a result, the weekly rule is less likely to incentivize drivers to drive during non-peak periods, to go to certain locations, or to drive during congested times.
154. In addition, the weekly rule gives ridesharing platforms the flexibility to find the least disruptive way of changing driver payments and rider fares to cover the cost of the Minimum Payment Requirement. The Per Trip Calculation Requirement of the Minimum Payment Rule imposes payment increases on specific trips without regard for the economic principles of optimal taxation — which inform how to design a policy to maximize social welfare — and therefore results in substantial distortions, as described in Sections V.B.i–ii. Under the weekly rule, ridesharing platforms can implement payment and fare changes more carefully to mitigate the distortionary effects on quantity. This is beneficial to drivers because it will minimize reductions in demand resulting from increased fares.

VI. RELYING ON PLATFORM-SPECIFIC UTILIZATION RATES MAY HAVE THE UNINTENDED EFFECT OF REDUCING COMPETITION

155. Parrott and Reich write that “the leading firm will become a natural monopoly only if its rider and driver network advantages are substantial enough to deter entry by competitors,” and that “policies

that nudge the industry in a more competitive direction are [...] justified.”¹⁹¹ However, they fail to evaluate whether the Minimum Payment Rule will “nudge the industry in a more competitive direction,” or instead do the opposite.

156. The most obvious implication of the requirement that individual platforms’ utilization be used to calculate a platform-specific floor for driver pay is that platforms with lower average driver utilization will have higher per trip costs. Small or entrant platforms with a smaller base of riders and drivers will have lower utilization than larger incumbents. Therefore, the Minimum Payment Rule could entrench large incumbents by ensuring that their smaller rivals have higher per trip costs, harming competition. Parrott and Reich’s failure to grapple with this important policy issue further demonstrates the unreliability of their conclusion that the policy “incentivizes driver utilization.”¹⁹²
157. Less competition between platforms may be detrimental to drivers. With less competition, ridesharing platforms will be less likely to compete for drivers by offering lower commission rates or fewer innovative driver-friendly features.¹⁹³ Less competition between platforms may also be detrimental to riders. With less competition, ridesharing platforms will be less likely to compete for riders by offering incentives or innovations that make ridesharing platforms more attractive to riders. Fewer riders and a reduction in the demand for trips will result in reduced earnings for drivers.

A. The Effect of Platform-Specific Utilization Rates Depends on Network Effects and Multi-Homing

158. As I discussed above in Section III.A, the ridesharing industry is characterized by network effects.¹⁹⁴ More drivers make a platform more appealing to riders, as they will get trips faster. By the same token, more riders make a platform more appealing to drivers, as they will be able to

¹⁹¹ Parrott and Reich Report, p. 42.

¹⁹² Parrott and Reich Report, p. 55.

¹⁹³ Lyft and Uber compete for riders by offering app improvements that benefit drivers, such as driver-set destinations, which allow drivers to choose a location they want to drive towards. Bhuiyan, Johana, “All the ways Lyft and Uber are competing to be the friendlier app for drivers,” *recode*, October 7, 2017.

¹⁹⁴ Tucker, “Network Effects and Market Power: What Have We Learned in the Last Decade?,” *Antitrust*, Vol. 32, No. 2 (2018).

provide more trips with less down time between. As a result, increasing the number of drivers and riders by the same proportion can make the whole platform more valuable as drivers and riders are matched with each other faster.¹⁹⁵ As an illustration, suppose there are two platforms in a city: Platform A and Platform B. If Platform B has twice as many drivers and twice as many potential riders who are located similarly across town, any single driver from Platform B will be closer to a customer compared to a driver from Platform A. Therefore, Platform B will have lower wait times for both drivers and riders, which translates into higher utilization.

159. This is a well-known phenomenon that is recognized by players in the industry. For instance, Uber Director of Policy Research Betsy Masiello explains: “As the number of passengers and drivers using Uber grows, any individual driver is more likely to be close to a rider. This means shorter pickup times and more time spent with a paying passenger in the back of the car.”¹⁹⁶ She shows that between 2014 and 2016, in Boston, Chicago, Los Angeles, New York City, and San Francisco, both rider and driver wait times decreased concurrently.
160. One direct consequence of such network effects is that larger ridesharing platforms are more likely to have lower wait times, both for riders and drivers, which implies a higher driver utilization. Ridesharing platforms new to the market are likely to have low utilization rates as they do not have the same rider base. At the moment, such newer entrants can potentially grow because of the presence of multi-homing by both drivers and riders. However, as I discuss below, the use of platform-specific utilization rates will limit their ability to grow.

B. Using Platform-Specific Utilization Rates May Hinder Entry of New Platforms and the Growth of Smaller Platforms, Thereby Reducing Competition

161. Using platform-specific utilization rates in the Minimum Payment Rule is likely to generate increased barriers to entry and increased barriers to expansion, making it harder for smaller or

¹⁹⁵ Nikzad, Afshin, “Thickness and Competition in Ride-sharing Markets,” (2017), (“One of the generic intuitions is that expanding both sides of a platform simultaneously could benefit both sides”).

¹⁹⁶ Masiello, Betsy, “Faster pickup times mean busier drivers,” *Uber Newsroom*, April 5, 2017, available at <https://www.uber.com/newsroom/faster-pickup-times-mean-busier-drivers/>.

newer platforms to compete. These barriers may entrench large incumbents and increase market concentration, which may hurt drivers and riders.

162. Ridesharing platforms need to create a large enough pool of riders and drivers. Platform entrants and smaller platforms, due to their small user bases, will likely have greater wait times for riders and drivers, translating into lower utilization rates for drivers and longer wait times for riders. However, it is typical for new entrants and smaller platforms to provide financial incentives for riders and drivers in order to attract them, until the platform has reached critical mass.¹⁹⁷ Their ability to do so is aided by both riders' and drivers' willingness to multi-home in the face of these incentives.
163. Under the proposed regime, once a ridesharing platform entrant passes the cutoff of 10,000 trips per day, it will need to pay its drivers according to the Minimum Payment Rule and the Per Trip Calculation Requirement.¹⁹⁸ Entrants reaching that size are likely to have low, though increasing, utilization rates. The per trip driver earnings on the platform of a new entrant will be much higher than that of its competitor platforms.¹⁹⁹ Similarly, the per trip driver earnings on the platform of smaller incumbents that have low utilization will increase more than those on the platforms of larger incumbents that have higher utilization. For instance, the implication of Juno's utilization rate of 50 percent, compared to Uber's rate of 58 percent, is that Juno's per trip minimum is 16 percent higher than Uber's.²⁰⁰
164. At least some of these higher costs are likely to be passed onto the riders in the form of higher fares, meaning that the smaller and newer platforms will struggle to attract riders. For example, while Juno's Minimum Payment Rule would be 16 percent higher than Uber's, its smaller

¹⁹⁷ Bhuiyan, Johana, "Lyft is on track to turn a profit, but will need to spend more to add riders and drivers as it expands," *recode*, January 13, 2017. Hawkins, "Juno wants to woo Uber drivers with a more ethical ride-sharing app," *The Verge*, March 29, 2016. Katz, "There's Only One Way to Compete With Uber," *WIRED*, September 2, 2016. Castro-Pagan, Carmen, "Uber, Lyft Competitors Share One Strategy: Perks for Drivers," *Bloomberg Law*, March 24, 2017.

¹⁹⁸ "Notice of Promulgation," 2018, p. 4.

¹⁹⁹ For instance, if a new entrant has a utilization rate of 29 percent, the payment implied by the Minimum Payment Rule will be twice as high as that required for Uber, which has a utilization of 58 percent. Parrott and Reich Report, p. 36.

²⁰⁰ $58/50 = 1.16$.

commission of 16.65 percent means that Juno would have little room to absorb those higher costs.²⁰¹

165. The Minimum Payment Rule may not be the most desirable pay structure for entrants or small platforms that need to entice both drivers and riders onto their platforms. For instance, the small platform may want to offer bonuses based on achieving a certain number of trips in a given time period. It might want to add payments that reassure drivers that even if there are no rider trips requested in the period they are driving, they will still receive some payment. In this case, the Minimum Payment Rule, by changing the pay structure of the small platform, is likely to create distortionary effects that will make it harder for the small platform to achieve scale.
166. If small platforms lose riders to the largest platforms, their utilization is likely going to decrease further, while that of the largest platforms will go up. This will improve the utilization of the largest platforms. This may create a vicious cycle, whereby the Minimum Payment Rule will further increase for the small platforms and decrease for the large platforms. This would result in the growth of the largest competitors to the detriment of the smallest competitors, increasing market concentration.
167. If despite these distortions, new entrants and smaller platforms were able to achieve some growth, their utilization rates would likely improve over time. However, since the Minimum Payment Rule is based on past utilization, there will always be a time lag between the current utilization rate, which measures how much drivers are driving (and thus earning), and the rate used in the per trip formula. This discrepancy in utilization rate will lead to driver earnings that are unnecessarily high relative to actual utilization levels, which will overshoot the objective Minimum Payment Requirement for smaller platforms. For instance, if a platform grows and is able to increase its utilization from 40 percent to 45 percent, the Minimum Payment Rule will be based off 40 percent even though the actual utilization is 45 percent. The time lag will cause the Minimum Payment Rule to be 12.5 percent higher than the Minimum Payment Requirement objective. The growing platforms' costs will therefore be inflated, acting as a drag for their growth, creating a further barrier to expansion. Conversely, in that scenario, despite losing market shares to the growing

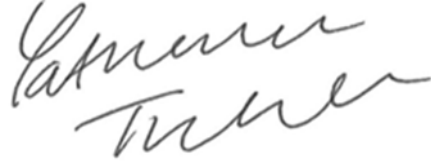
²⁰¹ "Fare breakdown," *Juno*, available at <https://help.gojuno.com/hc/en-us/articles/115003397945-Payment-Structure>.

platforms, large incumbents' costs would be anchored on higher utilization from the past, leading to a deflation of their costs.

VII. CONCLUSION

168. For the reasons I have explained in this report, it is my opinion that the Parrott and Reich Report is flawed and unreliable and the Supplementary Report fails to address the shortcomings of the initial Report. Neither report evaluates the effects of the Minimum Payment Rule and the Per Trip Calculation Requirement directly. Even accepting Parrott and Reich's method as a useful tool for evaluating the likely result of the policy, Parrott and Reich's own "simulation" predicts that the Minimum Payment Rule will decrease driver gross earnings once the flaws in their calculations are addressed.
169. The Minimum Payment Rule and the Per Trip Calculation Requirement both lack any economic basis and are likely to create a number of distortions in the market that Parrott and Reich fail to consider. The Per Trip Calculation Requirement is a blunt instrument that will have unintended negative consequences on drivers and riders alike, and a Per Week Calculation of the Minimum Payment Rule will result in fewer distortions while still achieving the Minimum Payment Requirement.
170. Platform-specific utilization rates in the Minimum Payment Rule are likely to generate increased barriers to entry and expansion. They will prevent new platforms from entering the market and smaller competitors from competing effectively. This may inadvertently entrench large incumbents, limit the ability of smaller platforms to compete, and reduce the dynamism of the market. In the long term, this could reduce competition and increase market concentration, which is likely to hurt drivers and riders.

I, Dr. Catherine Tucker, certify under penalty of perjury that the foregoing is true and correct to the best of my knowledge. If asked to testify under oath my testimony would be the same.

A handwritten signature in cursive script, appearing to read "Catherine Tucker", written in dark ink.

Catherine Tucker
January 29, 2019

Appendix A

CATHERINE TUCKER

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EDUCATION

Stanford University, Ph.D. in Economics (Advisor: Tim Bresnahan), 2005

Oxford University, BA in Politics, Philosophy and Economics, 1999

APPOINTMENTS

MIT Sloan, Sloan Distinguished Professor of Management Science, September 2015 –

MIT Sloan, Chair MIT Sloan PhD Program, July 2015 –

MIT Sloan, Professor of Management Science, July 2015 –

MIT, Co-Founder of the MIT CryptoEconomics Lab, 2018 -

National Bureau of Economic Research (NBER), Research Associate, September 2012 –

MIT Sloan, Mark Hyman Jr. Career Development Professor (with tenure), July 2012 –
September 2015

MIT Sloan, Associate Professor of Management Science, July 2011 – July 2015

National Bureau of Economic Research (NBER), Faculty Research Fellow, May 2011 –
September 2012

MIT Sloan, Douglas Drane Career Development Chair in IT and Management, July 2006 –

MIT Sloan, Assistant Professor of Marketing, July 2005 – June 2011

HONORS AND AWARDS

2018	ISMS Long Term Impact Award
2018	O'Dell Award
2018	MSI Scholar
2017	Congressional Testimony on 'Algorithms: How Companies' Decisions About Data and Content Impact Consumers'
2017	Nominated for Teacher of the Year award (Also in 2012, 2010 and 2009)
2015	Erin Anderson Award
2014	Paul E. Green Award
2013	Teacher of the Year Award, MIT Sloan
2013	Jamieson Prize for Excellence in Teaching
2012	Garfield Economic Impact Award for Best Paper in Health Economics
2011	WHITE Award for best paper in the Economics of Healthcare IT
2011	Public Utility Research Prize for the best paper in regulatory economics
2011	NSF CAREER Award
2011	MSI Young Scholar
2010	Management Science Distinguished Service Award
2004	Koret Foundation Scholar, Stanford Institute for Economic Policy Research Fellowship
2004	Fourth Annual Claire and Ralph Landau Student Working Paper prize

PUBLISHED/ACCEPTED PAPERS

1. 'Identifying Formal and Informal Influence in Technology Adoption with Network Externalities', *Management Science*, Vol. 55 No. 12, December 2008, pp. 2024-2039
2. 'Privacy Protection and Technology Diffusion: The Case of Electronic Medical Records' with Amalia Miller, *Management Science (Lead Article)*, Vol. 55 No. 7, July 2009, pp. 1077-1093
 - Republished as part of INFORMS 'Healthcare in the Age of Analytics' series
3. 'How Sales Taxes Affect Customer and Firm Behavior: The Role of Search on the Internet' with Eric Anderson, Nathan Fong and Duncan Simester, *Journal of Marketing Research*, Vol. 47 No. 2, April 2010, pp. 229-239
4. 'Growing Two-sided Networks by Advertising the User Base: A Field Experiment', with Juanjuan Zhang, *Marketing Science*, Vol. 29 No. 5, September-October 2010, pp. 805-814

5. 'Privacy Regulation and Online Advertising' with Avi Goldfarb, *Management Science*, Vol. 57 No. 1, January 2011, pp. 57-71
6. 'Search Engine Advertising: Channel Substitution when Pricing Ads to Context', with Avi Goldfarb, *Management Science*, Vol. 57 No 3, March 2011, pp. 458-470
7. 'Stuck in the Adoption Funnel: The Effect of Interruptions in the Adoption Process on Usage' with Anja Lambrecht and Katja Seim, *Marketing Science*, Vol. 30 No. 2, March-April 2011, pp. 355-36
8. 'Advertising Bans and the Substitutability of Online and Offline Advertising', with Avi Goldfarb, *Journal of Marketing Research (Lead Article)*, Vol. 48 No. 2, April 2011, pp. 207-227
9. 'Can Healthcare Information Technology Save Babies?' with Amalia Miller, *Journal of Political Economy*, Vol. 119 No. 2, April 2011, pp. 289-324
10. 'How Does Popularity Information Affect Choices? A Field Experiment' with Juanjuan Zhang, *Management Science*, Vol. 57 No. 5, May 2011, pp. 828-842
11. 'Online Display Advertising: Targeting and Obtrusiveness' with Avi Goldfarb, *Marketing Science (Lead Article and Discussion Paper)*, Vol. 30 No. 3, May-June 2011, pp. 389-404
 - 'Rejoinder - Implications of "Online Display Advertising: Targeting and Obtrusiveness' with Avi Goldfarb, *Marketing Science*, Vol. 30 No. 3, May-June 2011, pp. 413-415
 - Nominated for John D. C. Little Award
 - Nominated for Long Term Impact Award 2017
 - Long Term Impact Award 2018
12. 'Encryption and Data Security' with Amalia Miller, *Journal of Policy Analysis and Management*, Vol. 30 No. 3, Summer 2011, pp. 534-556
13. 'Paying With Money or With Effort: Pricing When Customers Anticipate Hassle' with Anja Lambrecht, *Journal of Marketing Research*, Vol. 49 No. 1, February 2012, pp. 66-82.
14. 'Heterogeneity and the Dynamics of Technology Adoption' with Stephen Ryan, *Quantitative Marketing and Economics*, Vol 10 No. 1, March 2012, pp 63-109
15. 'Shifts in Privacy Concerns', *American Economic Review: Papers and Proceedings* with Avi Goldfarb, Vol. 102 No. 3, May 2012, pp. 349-53

16. 'How does the Use of Trademarks by Intermediaries Affect Online Search?' with Lesley Chiou. *Marketing Science*, Vol 31 No. 5, September 2012, pp 819-837
17. 'Active Social Media Management: The Case of Health Care' with Amalia Miller. *Information Systems Research* Vol. 24, No. 1, March 2013, pp. 52-70
 - Republished as part of Informs 'Healthcare in the Age of Analytics' series
18. 'Paywalls and the Demand for News' with Lesley Chiou. *Information Economics and Policy* Volume 25 No. 2, June 2013, pp. 61-69
19. 'Days on Market and Home Sales' with Juanjuan Zhang and Ting Zhu. *RAND Journal of Economics* Volume 44 No. 2, pages 337-360, Summer 2013
20. 'When Does Retargeting Work? Timing Information Specificity' with Anja Lambrecht. *Journal of Marketing Research (Lead Article)* Vol. 50 No. 5, October 2013, pp. 561-576
 - Paul E. Green Award for the 'Best article in the Journal of Marketing Research that demonstrates the greatest potential to contribute significantly to the practice of marketing research.'
 - William O'Dell Award. This award honors the JMR article published in 2013 that has made the most significant, long-term contribution to marketing theory, methodology, and/or practice
21. 'Health Information Exchange, System Size and Information Silos' with Amalia Miller. *Journal of Health Economics*, Vol. 33 No. 2, January 2014: pp. 28-42
22. 'Electronic Discovery and the Adoption of Information Technology' with Amalia Miller. *Journal of Law, Economics, & Organization (Lead Article)*, Vol. 30. No. 2, May 2014, pp. 217-243
23. 'Social Networks, Personalized Advertising, and Privacy Controls.', *Journal of Marketing Research*, Vol. 51, No. 5, October 2014, pp. 546-562.
 - Citation of Excellence Award Emerald Publishing
24. 'Trademarks, Triggers, and Online Search' with Stefan Bechtold. *Journal of Empirical Legal Studies* Vol. 11 No. 4, December 2014
25. 'The Reach and Persuasiveness of Viral Video Ads' *Marketing Science* Vol. 34, No. 2 2015 pp. 281-296
26. 'Privacy Regulation and Market Structure' with James Campbell and Avi Goldfarb. *Journal of Economics & Management Strategy* Vol 24, No. 1, Spring 2015, pp 47-73

27. 'Standardization and the Effectiveness of Online Advertising' with Avi Goldfarb. *Management Science* Vol 61, No. 11, 2015, pp 2707-2719
 28. 'Harbingers of Failure' with Eric Anderson, Song Lin and Duncan Simester. *Journal of Marketing Research (Lead Article)* Oct 2015, Vol. 52, No. 5, pp. 580-592.
 29. 'The Effect of Patent Litigation and Patent Assertion Entities on Entrepreneurial Activity' with Stephen Kiebzaka. and Greg Rafert. *Research Policy* Vol 45, No. 1, February 2016, Pages 218-231
 30. 'When early adopters don't adopt' with Christian Catalini. *Science* Vol. 357, Issue 6347, 2017 pp. 135-136
 31. 'Network Stability, Network Externalities, and Technology Adoption' in *Advances in Strategic Management*, Volume 37, pp.151 - 175
 32. 'Should You Target Early Trend Propagators? Evidence from Twitter' with Anja Lambrecht and Caroline Wiertz (Lead Article). *Marketing Science* 2018 Vol. 37 No. 2 pp.177-199
 33. 'Digital Content Aggregation Platforms: The Case of the News Media.' with Lesley Chiou - Forthcoming at *Journal of Economics & Management Strategy*
 34. 'Privacy Protection, Personalized Medicine and Genetic Testing' with Amalia Miller. Forthcoming at *Management Science*
 35. 'Digital Economics' with Avi Goldfarb. Forthcoming at *Journal of Economic Literature*
 36. 'Algorithmic Bias? An Empirical Study into Apparent Gender-Based Discrimination in the Display of STEM Career Ads ' with Anja Lambrecht. Forthcoming at *Management Science*
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CHAPTERS IN EDITED VOLUMES AND SUMMARY PIECES

37. 'Modeling Social Interactions: Identification, Empirical Methods and Policy Implications' with Wes Hartmann, Puneet Manchanda, Harikesh Nair, Matt Bothner, Peter Dodds, David Godes and Karthik Hosanagar, *Marketing Letters*, Vol. 19 No. 3, December 2008, pp. 287-304
38. 'Search Engine Advertising - Examining a profitable side of the long tail of advertising that is not possible under the traditional broadcast advertising model' with Avi Goldfarb, *Communications of the ACM*, Vol. 51 No. 11, November 2008, pp. 22-24

39. 'Online Advertising', with Avi Goldfarb, *Advances in Computers*, Vol. 81, March 2011, Marvin Zelkowitz (Ed), Elsevier
40. 'Substitution between Online and Offline Advertising Markets', with Avi Goldfarb, *Journal of Competition Law and Economics*, Vol. 7 No. 1, March 2011, pp. 37-44
41. 'Online Advertising, Behavioral Targeting, and Privacy', with Avi Goldfarb, *Communications of the ACM*, Vol. 54 No. 5, May 2011, 25-27
42. 'Privacy and Innovation', *Innovation Policy and the Economy*, Vol. 11, 2012, Josh Lerner and Scott Stern (Eds), NBER
43. 'The Economics of Advertising and Privacy', *International Journal of Industrial Organization*, Vol. 30 No. 3, May 2012, pp. 326-329
44. 'Empirical Research on the Economic Effects of Privacy Regulation'. *Journal on Telecommunications and High Technology Law*, Vol. 10 No. 2, Summer 2012, pp. 265-272
45. 'Social Networks, Advertising and Antitrust', with Alex Marthews, *George Mason Law Review*, 2012, Vol 19 No 5., pp. 1211-1227.
46. 'Why Managing Customer Privacy Can Be an Opportunity' with Avi Goldfarb, *Spring 2013, Sloan Management Review*
47. 'The Implications of Improved Attribution and Measurability for Antitrust and Privacy in Online Advertising Markets', *George Mason Law Review*, Vol. 2 No. 2, pp. 1025-1054 (2013).
48. 'Privacy and the Internet' Chapter 11, *Handbook of Media Economics*, 2016 , Edited by Simon Anderson and Joel Waldfogel
49. Frontiers of Health Policy: Digital Data and Personalized Medicine, *Innovation Policy and the Economy*, Vol. 15, 2016, Josh Lerner and Scott Stern (Eds), NBER
50. 'Impacts of Surveillance on Behavior' with Alex Marthews, in Gray, David C. and Henderson, Stephen (Editors), 'The Cambridge Handbook of Surveillance Law' (2017).
51. 'Field Experiments in Marketing,' with Anja Lambrecht, *Handbook of Marketing Analytics*, Forthcoming
52. 'Can Big Data Protect a Firm from Competition?', CPI Chronicle, January, 2017 with Anja Lambrecht

53. Network Effects and Market Power: What Have We Learned in the Last Decade?
Antitrust Vol. 32 No 2., Spring 2018
54. 'Inequality, Privacy and Digital Market Design', Forthcoming chapter in 'Fair by Design' edited by Scott Kominers and Alex Teytelboym.
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BOOKS EDITED

55. Economic Analysis of the Digital Economy, University of Chicago Press, 2015, with Avi Goldfarb and Shane Greenstein
56. The Economics of Digitization, Edward Elgar Publishing, 2013., with Avi Goldfarb and Shane Greenstein
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POLICY WRITING

57. OECD Roundtable on Privacy, Report on the 'Economic Value of Online Information', December 2010
58. Written Congressional Testimony on 'Internet Privacy: The Impact and Burden of European Regulation,' U.S. House Energy and Commerce Committee, September 2011
59. Written Congressional Testimony on 'Algorithms: How Companies' Decisions About Data and Content Impact Consumers,' U.S. House Energy and Commerce Committee, November 2017
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PAPERS UNDER REVIEW

60. 'Social Advertising'. Revise and resubmit at *Management Science*
61. 'How Do Restrictions on Advertising Affect Consumer Search?' with Lesley Chiou. Revise and resubmit at *Management Science*
62. 'Patent Trolls and Technology Diffusion: The Case of Medical Imaging' Revise and resubmit at *RAND Journal of Economics*
63. 'Third-Party Certification: The Case of Medical Devices' with Cristina Nistor Revise and resubmit at *Management Science*

64. ‘Guns, Privacy and Crime’ with Alessandro Acquisti Revise and resubmit at *Information Systems Research*
65. The Surprising Breadth of ‘Harbingers of Failure’ with Duncan Simester and Clair Yang. Revise and resubmit at *Journal of Marketing Research*
66. ‘Tensile Promotions in Displays Advertising’ with Anja Lambrecht Revise and resubmit at *Quantitative Marketing and Economics*
67. ‘A New Method of Measuring Online Media Advertising Effectiveness: Prospective Meta-Analysis in Marketing’ with Gui Liberali, Glen L. Urban, Benedict G. Dellaert, Yakov C. Bart, and S. Stremersch.
68. ‘Personalizing mental fit for online shopping applications - How the success of recommendations depends on mental categorization and mental budgeting’ with Oliver Emrich and Thomas Rudolph
69. ‘The Digital Privacy Paradox: Small Money, Small Costs, Small Talk’ with Susan Athey and Christian Catalini
70. ‘Information Shocks and Internet Silos: Evidence from Creationist Friendly Curriculum’ with Ananya Sen
71. ‘Government Surveillance and Internet Search Behavior’ with Alex Marthews
72. ‘Does IT Lead to More Equal or More Unequal Treatment? An Empirical Study of the Effect of Smartphone Use on Social Inequality in Employee-Customer interactions’ with Shuyi Yu
73. ‘Antitrust and Costless Verification: An optimistic and a pessimistic view of the implications of blockchain technology’ invited at ‘Antitrust Law Journal: Innovative Antitrust with Christian Catalini
74. ‘How Effective Is Black-Box Digital Consumer Profiling And Audience Delivery?: Evidence from Field Studies’ with Nico Neumann and Tim Whitfield

WORK IN PROGRESS

Manuscripts

75. Health IT and Ambulatory Care Quality with Carole R. Gresenz, Scott Laughery, and Amalia R. Miller

76. 'Conducting Research with Quasi-Experiments: A Guide for Marketers' with Avi Goldfarb.

77. 'Testimonial Advertising on Social Networks to Existing Customers and New Customers' with Shuyi Yu

Data Analysis

78. 'Data Privacy and Children: An Empirical Study of Mobile Applications' with and G. Cecere, F. Le Guel, V.Lefrere, and Pai-Ling Yin

79. 'Big Bad Data: The Case of For-Profit College Advertising' with Avinash Gannamaneni and Avi Goldfarb

80. 'Policing and Social Media: How police response times vary with YouTube postings' with Arvind Karunakaran

81. 'The Circularity of Marketing Communications in the Marketing Funnel: Evidence from a Field Experiment' with Anja Lambrecht

82. 'Nationalism, Xenophobia, Globalization and Global Brand Reach' with Willem Smit

83. 'Sexism, Ageism and Social Media Usage' with Willem Smit

84. 'Spillovers from Product Failure' with Amalia Miller

85. 'The Role of Marketing in ICOs' with Christian Catalini

86. 'The Shifters and Virality of Hate Speech Online' with Uttara Ananthakrishnan

Data Collection

87. 'Mergers and Big Data: Evidence from Healthcare' with Amalia Miller

88. 'The Lack of Appeal of Cross-Partisan Appeals: Evidence from an Experiment on Facebook' with Christina Tucker

89. 'Can the way someone interacts with a new technology predict their future career?' with Christian Catalini

INVITED SEMINARS

Universities

1. November 2018, Marketing Group, HEC Paris, France
2. November 2018, Cass Business School, City University of London, UK
3. October 2018, Marketing Group, University of Amsterdam, Netherlands
4. October 2018, Marketing Group, King's Business School, King's College, London
5. September 2018, Marketing Group, University of Frankfurt, Germany
6. June 2018, Harbin Institute of Technology, China
7. February 2018, IS/OM Group, New York University, NY
8. November 2017, Marketing Group, Rochester University, NY
9. October 2017, Marketing Group, Maryland University, MD
10. May 2017, Marketing Group, Old Dominion University
11. April 2017, Marketing Group, University of Southern California
12. March 2017, Marketing Group, Arison School of Business, IDC, Israel
13. January 2017, Distinguished Speakers Series, McGill University, Canada
14. September 2016, Technology Group, Harvard Business School, MA
15. August 2016, Southern Jiatong University, Sichuan, China
16. May 2016, Chapman University, Marketing Group
17. April 2016, Carnegie Mellon University, Public Policy Group
18. April 2016, Harvard Business School, Entrepreneurial Management Group
19. March 2016, INSEAD, Marketing Group
20. March 2016, University of Paris-Sud, Privacy Research Group
21. March 2016, Vienna University of Economics and Business, Marketing Group
22. September 2015 University of Maryland, IS Group
23. June 2015, Marketing Group, University of Cambridge, UK
24. May 2015, Marketing Group, University of Texas at Dallas, TX
25. March 2015, Health Policy Group, Georgia State University, GA
26. March 2015, Marketing Group, University of Colorado, CO
27. February 2015, Strategy Group, University of North Carolina, NC
28. January 2015, Marketing Group, Emory University, GA
29. December 2014, OPIM, Wharton School of Management, PA
30. October 2014, Economics Department, Yale University, CT
31. September 2014, Marketing Group, Boston University, MA
32. March 2014, Technology Group, University of California at Berkeley, CA
33. January 2014, Marketing Department at Texas A&M
34. November 2013, Marketing Group, University of California at Berkeley, CA
35. October 2013, Marketing Group, Tulane University, LA
36. October 2013, Marketing Group, University of Houston, TX
37. May 2013, Tuck School of Management, Dartmouth University, NH
38. March 2013, Economics Department, University of Toulouse
39. March 2013, Marketing Group, Rotterdam University
40. March 2013, Economics Department, University of Zurich
41. March 2013, Marketing group, Georgia Tech
42. January 2013, Anderson School, UCLA
43. January 2013, Marketing Group, CMU
44. October 2012, Marketing Group, Stanford University
45. October 2012, Marketing Group, Columbia University

46. October 2012, Marketing Group, University of Texas at Austin
47. September 2012, Marketing Group, Harvard Business School
48. June 2012, Strategy Group, London Business School
49. March 2012, Marketing Group, Cornell
50. February 2012, IS Group, Indian School of Business
51. February 2012, Marketing Group, Wharton
52. January 2012, Marketing Group, UCLA
53. November 2011, Marketing Group, University of Rochester
54. October 2011, Marketing Group, University of Zurich
55. October 2011, Department of Law and Economics, Swiss Federal Institute of Technology, Zurich
56. May 2011, Marketing Group, National University of Singapore
57. May 2011, IS Group, National University of Singapore
58. May 2011, Strategy Group, LMU Munich
59. May 2011, Marketing Group, New York University
60. March 2011, Marketing Group, Florida University
61. February 2011, IS Group, New York University
62. November 2010, European School of Management and Technology
63. October 2010, Marketing Group, Yale University
64. October 2010, Networked Business Group, Harvard Business School
65. September 2010, TIES Group, MIT Sloan
66. July 2010, Department of Economics, University of Mannheim
67. March 2010, Marketing Group, Wharton School, University of Pennsylvania
68. January 2010, Marketing Group, University of Michigan
69. November 2009, Marketing Group, University of California at Berkeley
70. October 2009, Digital Business Seminar, MIT Sloan
71. December 2008, Marketing Group, MIT Sloan
72. November 2008, Marketing Group, Rady School of Business, UCSD
73. September 2008, Strategy Group, MIT Sloan
74. May 2008, Digital Strategy Group, Tuck School of Business, Dartmouth University
75. April 2008, Kellogg Management and Strategy Group, Northwestern University
76. March 2008, Marketing Group, Duke University
77. March 2008, Strategy Group, Chicago GSB
78. July 2007, Marketing Group, London Business School, London, UK
79. April 2007, Marketing Group, Chicago GSB
80. March 2007, Marketing Group, Rotman School, University of Toronto
81. November 2005, Economics Department, Harvard University
82. October 2004-February 2005 (Job Market): NYU Stern, University of Michigan, University of Arizona, University of British Columbia, Federal Reserve Board, Federal Reserve Bank of New York, Harvard Business School, Kellogg, MIT Sloan, Federal Reserve Bank of Chicago, Stanford Economics Department

Other

83. January 2018, IMF
84. December 2017, Technology Policy Institute

85. October 2016, Federal Communications Commission
86. April 2015, Federal Communications Commission
87. November 2014, Office of Research at the Consumer Financial Protection Bureau
88. April 2014, Big Data Working Group, The White House.
89. February 2014, Main Street Patent Coalition, Panel hosted at the Senate by Senator Orrin Hatch
90. July 2013, Federal Communications Commission
91. August 2012, DG Competition, European Commission, Brussels
92. August 2012, Technology Policy Institute Conference, Aspen
93. December 2011, Havas Digital, New York
94. June 2011, Eneca
95. September 2010, Federal Trade Commission
96. September 2010, Google European Public Policy Unit, Paris
97. July 2009, Information Technology and Innovation Foundation, Washington DC

PRESENTATIONS OF RESEARCH AT CONFERENCES

1. June 2018, Antitrust and Big Data, Penn Wharton China Center Conference, Beijing
2. June 2018, Marketing Science
3. May 2018, Boston College Digital Innovation Workshop
4. December 2017, Mobile Marketing and Big Data Conference, NYU
5. September 2017, NBER Economics of AI Conference
6. July 2017, BU Platforms Conference
7. July 2017, NBER Digitization Meetings
8. June 2017, Marketing Science
9. June 2017, Regulation of Algorithms, Berlin
10. May 2017, Boston College Digital Innovation Workshop
11. November 2016, ICANN Public Meetings
12. October 2016, Conference on Digital Experimentation, Cambridge, MA
13. September 2016, FTC Consumer Protection Conference, Washington, DC
14. September 2016, George Washington roundtable on Platforms, Washington DC
15. May 2016, Competing with Big Data, Brugel, Brussels, Belgium
16. April 2016, NBER Innovation and Policy, Washington DC
17. April 2016, Financial Services Roundtable, NYC
18. March 2016, Digitization Tutorial, NBER
19. January 2016, PrivacyCon, FTC Conference, Washington, DC
20. July 2015, NBER Law and Economics (co-author presented), Cambridge, MA
21. July 2015, NBER Economics of Digitization, Cambridge, MA
22. June 2015, 'The Future of Research in the Digital Society', French Ministry of Culture and Communication - Toulouse School of Economics, Paris, France
23. June 2015, Marketing Science, Baltimore, MD
24. June 2015, Doctoral Consortium, Baltimore, MD
25. March 2015, IP Leadership Conference, Washington, DC

26. February 2015, Patents in Theory and Practice, Washington, DC
27. June 2014, Marketing Science, Atlanta, GA
28. May 2014, Boston College Social Media Workshop, Boston, MA
29. January 2014, American Economic Association Meetings
30. July 2013, Marketing Science, Istanbul, Turkey
31. June 2013, Searle Center Conference on Internet Search and Innovation, Chicago, IL
32. April 2013, Brown University Mini-Networks Conference
33. February 2013, WSDM 2013 Conference (Keynote Speaker), Rome, Italy
34. January 2013, American Economic Association Meetings, San Diego, CA (Co-author presented)
35. December 2012, New York Computer Science and Economics Day
36. November 2012, Search and Competition Conference, Melbourne Australia
37. October 2012, Economics of Personal Data, (Keynote Speaker), Amsterdam
38. August 2012, Amsterdam Symposium on Behavioral and Experimental Economics
39. July 2012, Fudan University Marketing Research Symposium, China
40. June 2012, Searle Center Conference on Internet Search and Innovation, Chicago, IL
41. June 2012, Innovation, Intellectual Property and Competition Policy Conference, Tilburg, Netherlands
42. June 2012, Marketing Science, Boston, MA
43. June 2012, Social Media and Business Transformation, Baltimore, MD
44. May 2012, The Law and Economics of Search Engines and Online Advertising, George Mason University, Arlington, VA
45. February 2012, NBER Economics of Digitization (co-author presented), Cambridge, MA
46. January 2012, Symposium on Antitrust and High-Tech Industries, George Mason University, VA
47. January 2012, Patents, Standards and Innovation, Tucson, AZ
48. January 2012, Econometric Society Meetings, Chicago, IL
49. January 2012, AEA Meetings (2 papers), Chicago, IL
50. December 2011, Economics of Privacy Workshop, Boulder, CO
51. November 2011, Economics and Computation Day, Cambridge, MA
52. November 2011, HBS Strategy Research Conference, Boston, MA
53. November 2011, The Law and Economics of Internet Search and Online Advertising Roundtable, George Mason University, Arlington, VA
54. November 2011, Patents Statistics for Decision Makers, Alexandria, VA
55. October 2011, Workshop on Health IT and Economics, Washington, DC
56. October 2011, Innovation, Organizations and Society, University of Chicago, IL
57. October 2011, Direct Marketing Research Summit, Boston, MA
58. September 2011, Invited Session 'Economics and Marketing', EARIE, Stockholm, Sweden.
59. July 2011, NBER Economics of Digitization, Cambridge, MA
60. July 2011, SICS, Berkeley, CA
61. June 2011, The Law and Economics of Search Engines and Online Advertising, George Mason University, Arlington, VA
62. June 2011, Workshop on the Economics on Information Security, Washington, DC
63. June 2011, Marketing Science (3 papers), Houston, TX
64. June 2011, Searle Center Conference on Internet Search and Innovation, Chicago, IL

65. May 2011, Boston College Social Media Workshop, Boston, MA
66. May 2011, Technology Pricing Forum, Boston, MA
67. April 2011, NBER Innovation Policy and the Economy, Washington, DC
68. April 2011, International Industrial Organization Conference (3 papers), Boston, MA
69. March 2011, Technology Policy Institute, Washington, DC
70. February 2011, NBER Economics of Digitization (co-author presented), Palo Alto, CA
71. January 2011, Sixth bi-annual Conference on The Economics of Intellectual Property, Software and the Internet (2 papers, plenary speaker), Toulouse, France
72. January 2011, MSI Young Scholars Conference, Park City, UT
73. December 2010, Workshop on Information Systems and Economics, Washington University of St. Louis (co-author presented), St. Louis, MO
74. December 2010, OECD Economics of Privacy Roundtable, Paris, France
75. November 2010, Net Institute Conference, New York, NY
76. October 2010, Workshop on Media Economics and Public Policy (co-author presented), New York, NY
77. October 2010, Workshop on Health IT and Economics, Washington, DC
78. September 2010, ITIF and CAGW Privacy Working Group Meetings, Washington, DC
79. September 2010, Medical Malpractice Conference, Mohegan, CT
80. September 2010, Search and Web Advertising Strategies and Their Impacts on Consumer Workshop, Paris, France
81. July 2010, NBER Meetings (IT), Cambridge, MA
82. July 2010, NBER Meetings (Healthcare and IT), Cambridge, MA
83. July 2010, SICS, Berkeley, CA
84. July 2010, Keynote Speaker, 8th ZEW Conference on the Economics of Information and Communication Technologies, Mannheim, Germany
85. June 2010, American Society of Health Economists Conference, Cornell, NY
86. June 2010, Marketing Science (2 papers), Koeln, Germany
87. June 2010, Workshop on the Economics of Information Security (2 papers), Harvard, MA
88. January 2010, AEA Meetings, Atlanta, GA
89. December 2009, Workshop on Information Systems and Economics, Scottsdale, AZ
90. November 2009, WPP/Google Marketing Awards, Cambridge, MA
91. July 2009, NBER meetings (IT), Cambridge, MA
92. June 2009, IHIF Debate on Privacy, Washington, DC
93. June 2009, Marketing Science, Ann Arbor, MI
94. April 2009, International Industrial Organization Conference, Boston, MA
95. January 2009, Information Security Best Practices Conference, Philadelphia, PA
96. January 2009, Modeling Social Network Data Conference, Philadelphia, PA
97. July 2008, NBER Meetings (Productivity), Cambridge, MA
98. July 2008, SICS, Berkeley, CA
99. July 2008, Fourth Workshop on Ad Auctions, Chicago, MA
100. June 2008, Marketing Science, Vancouver, BC
101. May 2008, International Industrial Organization Conference, Richmond, VA
102. April 2008, Net Institute Conference, New York, NY
103. November 2007, NBER Health Meetings (Co-author presented), Boston, MA
104. July 2007, SICS, Berkeley, CA

105. June 2007, Workshop on the Economics of Information Security, Pittsburgh
106. June 2007, Choice Symposium, Philadelphia, PA
107. May 2007, eCommerce Research Symposium, Stamford, CT
108. April 2007, Net Institute Conference, New York, NY
109. April 2007, International Industrial Organization Conference, Savannah, GA
110. March 2007, Health Economics Conference, Tucson, AZ
111. February 2007, NBER Winter Meetings, Palo Alto, CA
112. January 2007, Economics of the Software and Internet Industries (2 Papers), Toulouse, France
113. October 2006, QME Conference, Stanford University, CA
114. June 2006, Marketing Science, Pittsburgh, PA
115. April 2006, International Industrial Organization Conference, Boston, MA
116. October 2005, NEMC Conference, Boston, MA
117. October 2005, TPRC Conference, Washington, DC
118. June 2005, CRES Industrial Organization Conference, Washington University in St. Louis, MO
119. July 2002, Payment Systems Conference, IDEI, Toulouse, France

PROFESSIONAL SERVICE

- **Associate Editor:** Management Science, Marketing Science, Journal of Marketing Research, International Journal of Research in Marketing
- **Associate Editor:** Information Systems Research, Special Issue on Social Media and Business Transformation
- **Departmental Editor:** Quantitative Marketing and Economics
- **Editor:** The Economics of the Internet, Palgrave Dictionary of Economics
- **Co-Editor:** NBER: The Economics of Digitization - An Agenda
- **Co-Editor:** Information Economics and Policy, Special Issue on Economics of Digital Media Markets
- **Editorial Review Board:** Journal of Marketing, ISR Special Issue on Managing Digital Vulnerabilities, Journal of Economic Literature
- **Conference Program Committees**
 - 2018 Co-organizer, NBER Conference on the Economics of Artificial Intelligence
 - 2018 Scientific Committee: ZEW Conference on the Economics of Information and Communication Technologies
 - 2018 Program Committee: Workshop on the Economics of Information Security
 - 2019 Scientific Committee: IP Statistics for Decision Makers
 - 2017 Scientific Committee: IP Statistics for Decision Makers
 - 2017 Scientific Committee: ZEW Conference on the Economics of Information and Communication Technologies
 - 2017 Program Committee: Workshop on the Economics of Information Security
 - 2016 Program Committee: Workshop on the Economics of Information Security
 - 2016 Scientific Committee: ZEW Conference on the Economics of Information and

Communication Technologies

- 2015 Scientific Committee: Competition, Standardization and Innovation
- 2015 Scientific Committee: Intellectual Property Statistics for Decision Makers
- 2015 Associate Editor: ICIS 2015, Healthcare track
- 2015 Scientific Committee: European Association for Research in Industrial Economics
- 2015 Program Committee: ACM Conference on Economics and Computation
- 2015 Program Committee: Workshop on the Economics of Information Security
- 2015 Chief-Organizer: Quantitative Marketing and Economics Conference
- 2015 Scientific Committee: ZEW Conference on the Economics of Information and Communication Technologies
- 2014 Scientific Committee: European Association for Research in Industrial Economics
- 2014 Scientific Committee: Conference on the Economics of Information and Communication Technologies
- 2014 Program Committee: International Conference on Big Data and Analytics in Healthcare
- 2013 Program Committee: Quantitative Marketing and Economics
- 2013 Scientific Committee: European Association for Research in Industrial Economics Conference
- 2013 Scientific Committee: Conference on the Economics of Information and Communication Technologies
- 2013 Program Committee: Workshop on the Economics of Information Security
- 2013 Associate Editor of Personal Data Markets Track: ECIS 2013
- 2012 Program Committee: European Association for Research in Industrial Economics Conference
- 2012 Program Committee (Conference Organizer) NBER: The Economics of Digitization Pre-Conference, June 2012
- 2012 Scientific Committee: Conference on the Economics of Information and Communication Technologies
- 2012 Senior Program Committee: 13th ACM Conference on Electronic Commerce
- 2012 Program Committee: Workshop on the Economics of Information Security
- 2011 Scientific Committee: European Association for Research in Industrial Economics Conference
- 2011 Scientific Committee: Conference on the Economics of Information and Communication Technologies
- 2011 Program Committee: Ad Auctions Workshop
- 2011 Program Committee: Workshop on the Economics of Information Security
- 2010 Program Committee: Workshop on IT and Economic Growth
- 2010 Program Committee: Conference on Health IT and Economics
- 2010 Program Committee: Workshop on the Economics of Information Security
- 2009 Program Committee: Workshop on the Economics of Information Security
- 2008 Program Committee: Workshop on the Economics of Information Security
- 2008 Program Committee: Ad Auctions Workshop

External Affiliations

- **Affiliate:** CESifo Research Network

- **Advisory Board:** Future of Privacy Forum
-

MIT SERVICE

- 2015- Faculty Chair, PhD program
 - 2015- EMBA Committee
 - 2015- ASB Committee
 - 2014- MIT Sloan Gender Equity Committee
 - 2013-2014 Group Head, Marketing Group
 - 2013-2014 Chair, Marketing Faculty Search Committee
 - 2013-2014 MIT Committee on Undergraduate Admissions and Financial Aid
 - 2011 North East Marketing Conference Coordinator
 - 2011 MIT Sloan Marketing Conference, Panel Moderator
 - 2011 Sloan Women in Management Conference, Panel Moderator
 - 2005, 2008, 2012 Marketing Faculty Search Committee
-

ADVISING

- 2019: Shuyi Yu, PhD Thesis supervisor
 - 2016: Abhishek Nagaraj, PhD Thesis advisor
 - 2012: Cristina Nistor, PhD Thesis advisor
 - 2010: Katherine Molina, Masters Thesis
 - 2008: Dinesh Shenoy, Masters Thesis
 - 2007: James Kelm, Masters Thesis
-

GRANTS AND SUPPORT

Academic Research Grants

2018	Sloan Foundation Grant (2018-2021), 'NBER Project on the Economics of Artificial Intelligence'. Principal Investigator	\$914,250
2017	Net Institute Grant	\$3,000
2016	Net Institute Grant	\$6,000
2013	MSI research Grant 4-1840	\$10,200
2011	Tilburg Law and Economics Center (TILEC) IIPC grant	\$21,000
2011	Google Grant	\$50,000
2011	Junior Faculty Research Assistance Program	\$30,000
2011	Net Institute Grant	\$6,000
2011	NBER Digitization Grant	\$20,000
2011	NSF CAREER Award	\$502,000
2010	Time-Warner Research Program on Digital Communications	\$20,000
2010	Net Institute Grant	\$6,000
2009	Net Institute Grant	\$6,000
2009	The James H. Ferry, Jr. Fund for Innovation in Research Education	\$50,000
2009	Google/WPP Grant	\$55,000
2008	Net Institute Grant	\$15,000
2007	Net Institute Grant	\$8,000
2006	Net Institute Grant	\$8,000

Industry Research Grants

2015	CCIA Research: Research into Sustainable Competitive Advantage and Big Data	\$60,000
2015	E-Logic: Research into Vertical Mergers and Patent Litigation	\$60,000
2014	CCIA Research: Research into Patent Litigation and Entrepreneurship	\$100,000
2012	Google Australia: Research into Measurement and Attribution	\$50,000

EXPERT TESTIMONY

- Confidential Cryptocurrency Matter
 - Expert Report (2018).
- In Re Disposable Contact Lens Antitrust Litigation. No. 3:15-md-2626-J-20JRK United States District Court, Middle District of Florida, Jacksonville Division
 - Expert Report and Deposition Testimony (2018).
- In Re Appraisal of AOL Inc: Consolidated C.A. No. 11204-VCG. Chancery Court of Delaware
 - Expert Report, Deposition and Trial Testimony (2017)
- Michael Edenborough v. ADT, LLC, d/b/a ADT Security Services, Inc. Case No: 3:16-cv-02233-JST United States District Court, Northern District of California, San Francisco Division
 - Declaration (2017).

- YETI Coolers, LLC, v. RTIC Coolers, LLC, et al. Civil Action No. 1:15-cv- 00597-RP United States District Court Western District of Texas Austin Division.
– Expert Report and Deposition Testimony (2016).
- Red Online Marketing Group LP, d/b/a 50onRED v. Revizer Ltd., d/b/a Ad Force Technologies, Ltd., and Revizer Technologies, Ltd. United States District Court, Eastern District of Pennsylvania Civil Action No. 14-1353
– Expert Report and Deposition Testimony (2016).
- Matthew Campbell and Michael Hurley et al. v. Facebook, Inc. Case No. C 13-05996 PJH. United States District Court Northern District of California
– Expert Report and Deposition Testimony (2016).
- GO Computer, Inc. et al. v. Microsoft Corporation Case No. CGC-05- 442684 Superior Court of the State Of California for the City and County of San Francisco
– Expert Report and Deposition Testimony (2015).
- Queen’s University at Kingston and PARTEQ Research and Development Innovations, v. Samsung Electronics Co., Ltd., et al. Civil Action No. 2:14-cv- 53-JRG- RSP.
– Expert Report and Deposition Testimony (2015).
- Yahchaaroah Lightbourne, on behalf of himself and all other similarly situated, Plaintiff, v. Printroom.com, Inc., Professional Photo Storefronts, Inc., Brand Affinity Technologies, Inc. and CBS Interactive Inc. E-2 Case No. SACV13-00876 JLS (RNBx) United States District Court, Central District of California.
– Expert Report (2015)
- In re: Chapter 11, Nortel Networks, Inc., et al., Debtors, U.S. Bankruptcy Court, District of Delaware, Case No. 09-10138(KG) (Jointly Administered), Re Dkt No. 13208. Deposition and Trial Testimony (2014)
– Expert Report, Deposition and Trial Testimony (2014).
- Angel Fraley, et al., Plaintiffs, v. Facebook, Inc., a corporation; and DOES 1-100, Defendants, U.S. District Court, Northern District of California, Case No. 5:11-cv- 01726-LHK. Deposition Testimony (2012)
– Expert Report and Deposition Testimony (2012).

TEACHING

- 15.818, Pricing (MBA Elective) 2006-
- 15.732, Marketing Management for Senior Executives 2012-
- 15.726, Pricing (EMBA Elective) 2012-
- 15.838, Doctoral Seminar, Spring 2006, Fall 2007, Fall 2013
- Marketing Management, Asian School of Business, 2016
- Guest Lecturer: HST.936: Health information systems to improve quality of care in resource-poor settings, 2014
- Executive Education: Blockchain Technologies: Business Innovation and Application, 2018-
- Executive Education: Marketing Innovation, 2016-
- Executive Education: Pricing 4dX, 2016-
- Executive Education: Strategic Marketing for the Technical Executive, 2012-2015

- Executive Education: Systematic Innovation of Products, Processes, and Services, 2013-
- Executive Education: Platform Strategy: Building and Thriving in a Vibrant Ecosystem, 2014-
- Executive Education: Global Executive Academy (multi-language), 2013, 2014
- Executive Education: Entrepreneurship Development Program, 2012-
- Faculty Coach, Takeda Leadership Academy, 2016-18

Appendix B

Materials Relied Upon

Public Documents

- “4 Apps that Compare Rideshare (Uber, Lyft, Juno, etc.) Prices and Wait Times,” *HelloTech: The Plug* (September 10, 2018), <https://www.hellotech.com/blog/4-apps-that-compare-rideshare-uber-lyft-juno-etc-prices-and-wait-times/>.
- “2018 Uber and Lyft Survey Results,” *The Rideshare Guy*, available at <https://therideshareguy.com/2018-uber-and-lyft-driver-survey-results-the-rideshare-guy/>, accessed January 15, 2019.
- “AAA’s Your Driving Costs,” AAA, available at <https://exchange.aaa.com/automotive/driving-costs/#.XEuvnFxKhaQ>, accessed January 25, 2019.
- “About Shared rides,” *Lyft Help*, available at <https://help.lyft.com/hc/en-us/articles/115013078848-About-Shared-rides>, accessed January 22, 2019.
- “About the Rideshare Guy: Harry Campbell,” *The Rideshare Guide*, available at <https://therideshareguy.com/about-the-rideshare-guy/>, accessed January 26, 2019.
- “About Us,” *Kelley Blue Book*, available at <https://www.kbb.com/company/about-us/>, accessed January 26, 2019.
- “Auto Loan Calculator,” *Bank of America*, available at <https://www.bankofamerica.com/auto-loans/auto-loan-calculator/>, accessed January 25, 2019.
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- Bhuiyan, Johana, “All the ways Lyft and Uber are competing to be the friendlier app for drivers,” *recode*, October 7, 2017, available at <https://www.recode.net/2017/10/7/16363448/uber-lyft-driver-features-app>.
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- Bhuiyan, Johana, “Uber’s new ‘Express Pool’ is all about getting more riders to share rides,” *recode*, February 21, 2018, available at <https://www.recode.net/2018/2/21/17032598/uber-express-pool-transit-bus-cheaper>.

- Bliss, Laura, “How to Fix New York City’s ‘Unsustainable’ Traffic Woes,” *CityLab*, December 21, 2017, available at <https://www.citylab.com/transportation/2017/12/how-to-fix-new-york-citys-unsustainable-traffic-woes/548798/>.
- Buhr, Sarah, “Lyft Line Gets Into Perpetual Ride Territory With Triple Match Service,” *TechCrunch*, July 29, 2015, available at <https://techcrunch.com/2015/07/29/lyft-line-gets-into-perpetual-ride-territory-with-new-triple-match-service/>.
- Bushnell, Mona, “Should Your Restaurant be on GrubHub?,” *Business.com*, January 8, 2018, available at <https://www.business.com/articles/is-grubhub-good-for-restaurants/>.
- Busse, Meghan, and Marc Rysman, “Competition and Price Discrimination in Yellow Pages Advertising,” *RAND Journal of Economics*, Vol. 36, No. 2.
- Campbell, Harry, “10 Things I Learned At My Postmates Orientation,” *The Rideshare Guy* (April 13, 2015), <https://therideshareguy.com/10-things-i-learned-at-my-postmates-orientation/>.
- Campbell, Harry, *The Rideshare Guide: Everything You Need to Know about Driving for Uber, Lyft, and Other Ridesharing Companies*: Skyhorse Publishing, 2018.
- “Car Values,” *Kelley Blue Book*, available at <https://www.kbb.com/car-values/>, accessed January 26, 2019.
- Carlton, Dennis W., and Jeffrey M. Perloff, *Modern Industrial Organization*, 4 ed.: Pearson, 2005.
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- “Driver Pay,” *New York City Taxi & Limousine Commission*, available at http://www.nyc.gov/html/tlc/html/industry/driver_pay.shtml, accessed January 15, 2019.
- “Earnings Guarantee Promotions,” *Lyft*, available at <https://help.lyft.com/hc/en-us/articles/115012927247-Earnings-Guarantee-promotions>, accessed January 11, 2019.
- “Elevate Your Earnings With Lyft Lux and Lyft Lux SUV,” *Lyft: The Hub* (May 25, 2017), <https://thehub.lyft.com/blog/lux>.
- “Faculty Early Career Development Program,” *National Science Foundation*, available at https://www.nsf.gov/funding/pgm_summ.jsp?pims_id=503214, accessed January 11, 2019.

- “Fare breakdown,” *Juno*, available at <https://help.gojuno.com/hc/en-us/articles/115003397945-Payment-Structure>, accessed January 29, 2019.
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- Hall, Jonathan V., John J. Horton, and Daniel T. Knoepfle, “Labor Market Equilibrium: Evidence from Uber,” (2017).
- Hall, Jonathan V., John J. Horton, and Daniel T. Knoepfle, “Pricing Efficiently in Designed Markets: Evidence from Ride-Sharing,” (2018).
- Hall, Robert E., “New Evidence on the Markup of Prices Over Marginal Costs and the Role of Mega-Firms in the U.S. Economy,” (National Bureau of Economic Research, 2018).
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- “How much will I be paid as a contributor to Shutterstock?,” *Shutterstock*, available at https://www.shutterstock.com/contributorsupport/articles/en_US/kbat02/000006640?l=en_US, accessed January 25, 2019.
- “How surge pricing works,” *Uber*, available at <https://www.uber.com/drive/partner-app/how-surge-works/>, accessed January 25, 2019.
- “Int. No. 890-B For-Hire Vehicle Driver Wage,” *New York City Council* (2018).
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- Katz, Miranda, “This App Lets Drivers Juggle Competing Uber and Lyft Rides,” *WIRED*, February 15, 2018, available at <https://www.wired.com/story/this-app-lets-drivers-juggle-competing-uber-and-lyft-rides/>.
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Appendix C

Change in Gross Driver Pay after Accounting for Quantity and Utilization

1. To quantify the change in driver earnings, Parrott and Reich must account for the change in total driving hours, which is not the same as the change in number of trips.

2. Driver earnings can be expressed as follows:

$$\text{Driver Earnings} = \text{Hourly Earnings} \times \text{Total Driving Hours} \quad (1)$$

$$\text{Driver Earnings} = \text{Hourly Earnings} \times \frac{\text{Number of Trips}}{\text{Trips per Hour}} \quad (2)$$

3. The number of trips per hour can be expressed as a function of the utilization rate:

$$\text{Trips per Hour} = \frac{\text{Number of Trips}}{\text{Total Driving Hours}}$$

$$\text{Trips per Hour} = \frac{\text{Number of Trips} \times \text{Average Trip Duration}}{\text{Total Driving Hours} \times \text{Average Trip Duration}}$$

$$\text{Trips per Hour} = \frac{\text{Total Trip Duration (in hours)}}{\text{Total Driving Hours} \times \text{Average Trip Duration}}$$

$$\text{Trips per Hour} = \frac{\text{Utilization Rate}}{\text{Average Trip Duration}} \quad (3)$$

4. Combining the driver earnings equation (2) with equation (3), it is then clear that driver earnings in Parrott and Reich's model depends on the change in three key factors: a) hourly earnings, b) number of trips, and c) the utilization rate.

$$\text{Driver Earnings} = \text{Hourly Earnings} \times \frac{\text{Number of Trips}}{\text{Utilization Rate}} \times \text{Average Trip Duration} \quad (4)$$

5. Assuming average trip duration is unchanged, a change in driver earnings in Parrott and Reich's "simulation" can be calculated from the change in hourly earnings (+13.2 percent), the change in number of trips (-6.0 percent) and the change in utilization (+6.9 percent) as follows:

$$\begin{aligned} \text{Predicted Driver Earnings} &= \text{Hourly Earnings} \times (1 + 0.132) \\ &\times \frac{\text{Number of Trips} \times (1 - 0.060)}{\text{Utilization Rate} \times (1 + 0.069)} \end{aligned} \quad (5)$$

$$\textit{Predicted Driver Earnings} = (1 - 0.005) \times \textit{Baseline Driver Earnings} \quad (6)$$